

**PILOT STUDY ON FACTORS AFFECTING PIKA POPULATIONS
IN THE NORTH CASCADES ECOSYSTEM**

FINAL REPORT

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Photo by Jason Bruggeman

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ABSTRACT

The American pika (*Ochotona princeps*) is a small mammal primarily constrained to alpine and subalpine, or high elevation or latitude, regions in western North America. Because of their sensitivity to high temperatures and restricted habitat requirement of talus patches, pikas are considered to be an indicator species for climate change. Little is known about pika populations and their habitat use in the North Cascades ecosystem encompassing the North Cascades National Park Service Complex (NOCA) in Washington. The goal of this study was to address this need for information by conducting a one-year study to investigate climate, habitat, and human-related factors affecting pika populations throughout NOCA. Surveyors gathered data from late June through September 2009 on pika abundance, habitat attributes, and temperature in 115 talus patches contained within 30 1-km² survey areas.

Surveyors found active pika presence in 90% of survey areas with abundance per area ranging from 0 to 101 individuals (mean = 23.6; standard error [SE] = 4.6). Within the 30 areas, surveyors counted a total of 707 pikas in 115 talus patches, of which 74% had active pika presence. Surveyors found pikas in patches ranging in elevation between 351 and 2,130 m (mean = 1,457; SE = 44), which spanned the entire range of elevations for patches surveyed. I used statistical modeling and information theoretic techniques to examine climate, habitat, and anthropogenic factors influencing large-scale variation in pika abundance, and small-scale variation in abundance and the probability of talus patch use. On large scales, total pika abundance in survey areas was positively correlated with elevation, suggesting that higher elevation survey areas supported more pikas. On large and small scales, abundance was positively correlated with talus patch perimeter, suggesting resource availability may be an influential factor. On small scales, temperatures at and below the talus surface influenced abundance in patches. Abundance was negatively correlated with the minimum temperature recorded beneath the talus surface, suggesting as sub-surface temperatures increase, pika abundance decreases. Also, abundance was positively correlated with the maximum temperature recorded at the talus surface and negatively correlated with an interaction between the maximum temperature and date, suggesting abundance increased with temperature only to a certain point, and further increases in temperature resulted in decreased abundance. The probability of talus patch use by pikas was positively correlated with the distance to the nearest trail, indicating that the probability of pikas occupying a patch was greater in patches farther from trails.

This work also offers recommendations for future monitoring of pika populations in NOCA. To assess survey and sampling designs, I used data from replicate surveys to document factors affecting variability in the number of pikas counted per survey. The date of the survey was positively correlated with the number of pikas counted in each survey area, suggesting pika detectability increases as the summer progresses. I also conducted power analyses to determine the smallest detectable percent decline in mean pika population size. Based on the sample size of 30 survey areas and variability documented in mean pika abundance in areas in 2009, a 50% decrease in mean abundance is detectable at a power of 0.8. Because pika populations were affected by multiple climate and habitat factors on large and small scales, the potential exists for pikas to be adversely affected by climate change in NOCA. Continued annual monitoring and habitat data collection is required to determine population trends and further elucidate the factors affecting pika populations across multiple spatial scales.

1. INTRODUCTION

Climate change may alter the availability of resources and suitable habitats for species, which can subsequently affect the viability of populations (Hughes 2000, Schwartz et al. 2006). Therefore, comprehending how climate impacts wildlife populations is of primary importance to ecologists and natural resource managers (Root and Schneider 2006). Because climate affects vegetative communities, projected increasing temperature over time may result in distribution shifts for some vegetation species to higher elevations or latitudes (Root et al. 2003). In turn, this change in vegetation may cause a species to alter its range to coincide with preferred forage availability given sufficient habitat connectivity to allow for these movements (Parmesan and Yohe 2003). Critical alterations in habitat resources may also result from climate change with prominent examples from polar latitudes such as impacts from loss of sea ice on polar bears (*Ursus maritimus*) in the Arctic (Stirling et al. 1999) and penguins in the Antarctic (Barbraud and Weimerskirch 2001). Range-restricted species, such as those limited to alpine and polar regions, may be the most affected by climate change with extinction in some already chronicled (Parmesan 2006). Because of a limited ability to expand their ranges owing to geographical or physical barriers, range-restricted species may suffer range contractions, which may then result in smaller populations and a greater chance of extirpation or extinction.

Small mammals may be affected by climate change in different ways depending on the species. While low elevation habitat generalists may expand their range into higher elevations, habitat specialists, especially those that are patchily distributed, at higher elevations may face range contractions owing to resource limitations. In Yosemite National Park, Moritz et al. (2008) documented range contractions influenced by climate change in 50% of high elevation, small mammal species between the 1910s and 2000s. Additionally, no range shifts to higher elevations occurred for these species. In contrast, 50% of low elevation species expanded the upper elevation limits of their ranges, most notably species with short life spans and high reproductive rates (Moritz et al. 2008). A study of species richness of a small mammal community in the Great Basin in the Middle Holocene, during which climate was warmer and drier, offer insights into potential consequences of climate warming. Grayson (2000) documented a decrease in species richness affected by local extinctions coupled with increasing abundance of small mammals adapted to warm, dry conditions. Species requiring cool, moist environments were the most negatively affected (Grayson 2000).

The American pika (*Ochotona princeps*) is a small lagomorph primarily constrained to alpine and subalpine, or high elevation or latitude, regions in western North America (Smith and Weston 1990), although some lower elevation populations still exist (Beever et al. 2008). Pika habitat encompasses talus patches surrounded by, or containing, meadows or shrubs that offer vegetation for foraging and stocking haypiles, which provide a source of food throughout the winter when pikas rely on the thermal cover of snow over talus to survive (Dearing 1997, Morrison et al. 2009). Pikas establish territories as individuals in talus patches and are central-place foragers that rarely forage > 6 m from talus to minimize predation risk (Morrison et al. 2004, McIntire and Hik 2005). Pikas are considered to be a climate change indicator species (Beever et al. 2003, Smith et al. 2004) because of their restricted range and habitat requirements, and sensitivity to high temperatures (MacArthur and Wang 1974, Smith 1974b). Climate warming since the Holocene has been implicated in affecting current pika distributions throughout North America, with increasing temperatures resulting in pikas moving to higher elevations and latitudes in some areas (Beever et al. 2003, Grayson 2005).

Climate warming may affect pikas in multiple ways, including through impacts on vegetation, affecting the timing of initiating haying behavior, and behavioral changes owing to thermoregulation needs. Because of the potential climate related threats to the species, pikas have recently been petitioned for listing under the Endangered Species Act and the status of the species is currently under review (Federal Register 2009). Considered to be generalist herbivores, pikas concurrently select two diets during summer with the first consumed immediately while grazing (Dearing 1996). The second diet, collected during haying, is more specialized and higher in plant secondary compounds, such as phenolic chemicals that are toxic at high levels, to help preserve forage in winter (Dearing 1996, 1997). Increasing temperature or altered precipitation patterns during the growing season may affect plant species composition and abundance (Parmesan 2006), which may impact summer and winter food resources for pikas and result in range contractions to higher elevations. The phenology of haying behavior varies across elevations with haying beginning up to six weeks earlier at low compared to high elevations (Smith 1974b). Pikas begin haying once plant biomass peaks in an area and the amount of time spent haying increases throughout the summer (Huntly 1987). Increasing temperatures have been attributed to earlier vegetation green-up and peaks in biomass (Parmesan 2006), and, thus, pikas may begin haying earlier at all elevations should climate warming persist.

This may reduce the amount of time available grazing to meet summer energy requirements, which may result in lower survival. Finally, high temperatures limit pika activity and pikas may reduce the amount of time spent foraging during the middle of the day if temperatures make thermoregulation difficult (MacArthur and Wang 1974, Smith 1974b). A decrease in foraging time during summer may make it difficult for pikas to meet summer energy needs and stock haypiles for winter, which may reduce survival.

While long-term data exists on a few pika populations in Yukon, Canada (Morrison and Hik 2008a), the Great Basin (Beever et al. 2003), and the Sierra Nevada (Moilanen et al. 1998), extremely little is known about pika populations and habitat use in the Pacific Northwest, especially in the North Cascades ecosystem encompassing the North Cascades National Park Service Complex in Washington. Given the unknown status of the species and potential impacts of climate change, research on pikas has been one of the highest priorities for North Cascades managers and biologists to assist in understanding how climate warming may affect pikas. The goal of this study was to address this need for information by conducting a one-year study to investigate climate, habitat, and human-related factors affecting pika populations throughout the North Cascades National Park Service Complex. This research provides insights into mechanisms influencing pika populations across multiple spatial scales in several ways. First, I assessed the relative contributions of resource availability, temperature, snow, and proximity to campsites to large-scale variation in pika abundance in 1-km² survey areas. Second, I analyzed factors affecting variation in pika abundance on small scales and the probability of talus patch use. To accomplish this, I quantified how pika abundance in patches and the probability of patch use are correlated with patch habitat characteristics, resource availability, proximity to trails, and maximum and minimum temperatures at and below the talus surface, respectively. Finally, I examined habitat and temporal factors affecting temperature changes between the talus surface and sub-surface to help understand how patch characteristics, time, and date may affect the thermoregulation capabilities of pikas. This work also offers recommendations for future monitoring of pika populations in the North Cascades. To assess survey and sampling designs, I used data from repeated surveys to document factors affecting variability in the number of pikas counted per survey. I also conducted power analyses to determine the smallest detectable percent decline in mean pika population size. Overall, this work provides new and meaningful

insights into pika ecology from previously unstudied pika populations in the North Cascades ecosystem, and outlines considerations for future pika monitoring in the park.

2. METHODS

2A. Study Area

The North Cascades National Park Service Complex (NOCA) is located in north central Washington (Figure 1). Glacially sculpted valleys situated amidst rugged mountain ranges characterize the park with elevations ranging between 300 and 2,800 m. The park has two divides, the Cascade and Picket Crests, that affect weather patterns with highest amounts of precipitation occurring to the west of both divides and the least to the east of the Cascade Crest. There is a precipitation gradient extending eastward from Puget Sound through the Cascades, with precipitation peaking near the divides and declining on the eastern side of both crests. Between the two divides is a transition region of both wet and dry forest species. Because of the divides and wide range in elevation, the park contains a number of life zones (Pojar and MacKinnon 2004). The hemlock (*Tsuga* spp.) - western redcedar (*Thuja plicata*) - Douglas fir (*Pseudotsuga menziesii*) zone is located in river valleys < 600 m. The silver fir (*Abies amabilis*) zone exists in mountain forests at elevations of 600 to 1,700 m. The subalpine zone is located in mountain meadows at elevations between 1,200 and 2,100 m, while the alpine zone exists at elevations > 2,100 m (Pojar and MacKinnon 2004).

In NOCA, summers are generally temperate and dry, while winters are moderately cold and snowy. The SNOTEL station at Thunder Basin (elevation 1,317 m; 48.52 latitude, -120.983 longitude; Natural Resources Conservation Service [NRCS] 2009), located in between the two divides, provides an indication of climate variability in the park. In 2009 the average maximum daily temperature for July and August was 68.8°F, while between 1989 and 2009 it ranged from 61.7 to 74.0°F (mean = 68.2; standard error [SE] = 0.8; NRCS 2009). Total precipitation for May and June in 2009 was 14.2 cm with a historical mean of 13.3 cm (SE = 1.0) and range of 3.6 to 26.7 cm between 1988 and 2009 (NRCS 2009). Total summer precipitation for the months of July and August in 2009 was 9.9 cm with a historical range of 1.5 to 43.4 cm (mean = 9.9; SE = 1.9) between 1988 and 2009 (NRCS 2009). From December 2008 through February 2009 the average maximum daily temperature was 33.1°F, while historical values ranged from 29.9 to 38.1°F (mean = 33.5; SE = 0.5) between 1989 and 2009 (NRCS 2009). In winter 2009 the

maximum snow pack snow water equivalent (SWE) was 0.56 m with a historical range of 0.45 to 1.23 m (mean = 0.83; SE = 0.06) between 1989 and 2009 (NRCS 2009). The cumulative snow pack SWE for October 1, 2008 through May 31, 2009 (i.e., the sum of each day's individual SWE measurement) was 62.5 m, while historically cumulative SWE ranged from 48.0 to 166.5 m (mean = 103.3; SE = 7.3) between 1989 and 2009 (NRCS 2009). Cumulative SWE offers an index of winter severity because it provides a measure of the total snow on the ground for each day of the winter, but with each day's measurement added to that from preceding days to also account for the duration of snow on the ground.

2B. Sampling Design

To establish a sampling universe, I used Geographic Information Systems (GIS) techniques in ArcGIS 9.2 (ESRI 2006) to create a grid of 2,598 1-km² square survey areas across NOCA. For each survey area I calculated the mean elevation and nearest distance to a trail or road, and determined whether it is located west, east, or in between of the park's Cascade Crest and Picket Crest divides. The average of the mean elevation for all 2,598 survey areas was 1,334 m (SE = 9.4). I removed 918 survey areas that are > 3 km from a road or trail (35% of areas) from the sampling universe owing to safety concerns, and the high cost and extensive time required to access these locations in the park. The average mean elevation of the 918 removed survey areas was 1,520 m (SE = 13.2). I used NOCA landform GIS data (Riedel and Probala 2005) and U.S. Department of Agriculture National Agriculture Imagery Program 1 m satellite imagery to identify potential talus patches within the remaining 1,680 survey areas, which had an average mean elevation of 1,233 m (SE = 11.8). The 819 survey areas without any habitat classified as potential talus were removed from the sampling universe. I then assigned the remaining 861 survey areas, which had an average mean elevation of 1,457 m (SE = 13.9) to one of 15 strata (Appendix A; Table A1) based on a combination of mean elevation (≤ 913 m; 914-1,218 m; 1,219-1,523 m; 1,524-1,827 m; $\geq 1,828$ m) and location relative to the divides (west; middle; east).

I conducted a preliminary power analysis (Peterman 1990) to examine the effect of sample size on the ability to detect an annual decline in mean pika abundance across a sample of survey areas with a power of 0.8 and significance level, α , of 0.05. I considered ten different effect sizes (d) ranging from 0.1 to 1.0 and for each I examined three coefficient of variation

(CV) values to account for low (CV = 0.25), medium (CV = 0.5), and high (CV = 1.0) levels of variability in the data. The CV is defined as the standard deviation (SD) divided by the mean. Together, the effect size and CV determine the percent change in mean abundance, which is equal to $100 \cdot d \cdot CV$. To detect an effect size ≤ 0.5 , a sample of ≥ 26 survey areas are needed, while an effect size of ≤ 0.3 requires ≥ 70 survey areas. I conducted a second power analysis to examine sample sizes, or number of data points, required for a multiple regression model to provide a power of 0.8 at $\alpha = 0.05$ with various R^2 values and numbers of covariates in the model. Low levels of variability in the data (i.e., $R^2 \leq 0.1$) can only be explained with sample sizes of ≥ 72 and ≥ 117 for one and five covariate models, respectively. At $R^2 \geq 0.2$, sample sizes ≤ 52 are sufficient for a power of 0.8 for five covariate models. Based on results of the power analyses and resources available for 2009 surveys, I chose a sample size of 30 survey areas. I selected the sample of 30 areas (Figure 2) using a stratified random sampling design with proportional allocation across the 15 strata (Thompson 2002).

2C. *Pika Surveys and Data Collection*

Field crewmembers conducted pika surveys in the 30 survey areas from late June through September 2009. I divided each 1-km² survey area into 100 100-m x 100-m survey squares and identified those with potential talus habitat. Because each survey area contained different amounts of potential talus habitat, the number of survey squares varied among areas. Within each survey square containing potential pika habitat I placed points at corners of a 50-m x 50-m square such that the points were spaced 50 m apart and 25 m from the edge of the survey square. Surveyors navigated to each of the points to scan the area for pika habitat and locate talus patches. Upon location of a talus patch, surveyors mapped the patch boundary onto a laminated satellite photo of the survey area at 1:3,000 scale. Points without talus habitat were marked as non-habitat. Because a patch may consist of a mosaic of meadow and talus, and pika home ranges are < 25 m in radius (Smith 1974a, 1980), talus areas had to be separated by > 25 m to be classified as different patches. Surveyors intensively examined each patch for pika presence and pikas were counted by recording sightings, the presence of calling individuals at and below the talus surface, and active haypiles. Because pikas often build multiple haypiles, care was taken not to multiple count pikas for locations determined from active haypiles. Any haypiles within 25 m of the haypile location were assumed to belong to the same pika. If possible, surveyors

used visual observations of haying pikas to help clarify what haypiles belonged to each individual. Surveyors recorded pika locations in latitude/longitude coordinates using a Global Positioning System (GPS), the time of the sighting, and the air temperature at the location using a Hanna Instruments 93510 temperature meter. In patches that had no active pika presence, but did have pika sign from previous years (e.g., old haypiles or scat), surveyors recorded the location of the old sign with a GPS. For each location, surveyors recorded the weather as cloudy, mostly cloudy, partly cloudy, rainy, or sunny. Eight of the 30 survey areas were surveyed up to three times, with surveys occurring on different dates, to document variability in pika abundance throughout the summer. For these repeat surveys, surveyors navigated directly to talus patches that were identified and mapped on the first visit to the survey area. The remaining 22 areas were surveyed once during the summer.

At a random sample of up to four pika locations within each patch, surveyors recorded habitat and temperature data in 1-m² plots located every 5 m along a 25-m transect. In patches without active pika presence, but with old pika sign, surveyors completed one transect at the location of the sign. In patches without a pika detection, surveyors completed one transect at a random location. Within each plot surveyors recorded the vegetation categories present and corresponding percent cover, with cover assigned to one of six ranges: 0-5%, 5-25%, 25-50%, 50-75%, 75-95%, or 95-100% (Daubenmire 1959). Surveyors classified vegetation as graminoids, forbs (non-cushion plants), cushion plants, ferns, bryophytes, lichens, shrubs, trees, woody debris, or forest litter (e.g., leaves; needles) using Pojar and MacKinnon (2004). When ground, small rocks (< 0.2 m diameter), talus (0.2 to 1 m; Smith and Weston 1990), or large rocks (> 1 m) were present, surveyors recorded the amount of cover of each. When plots were comprised of talus, surveyors recorded the maximum talus depth, and the temperature at the talus surface and at depths of 0.5 m and 1 m using a Hanna Instruments 93510 temperature meter with a probe. When talus was < 0.5 m deep, surveyors recorded the temperature at the maximum depth. When talus was between 0.5 m and 1 m in depth, surveyors recorded the temperature at the maximum depth.

2D. Model Development and Statistical Analyses

2D.1. Covariate Development. Using the talus patch boundary maps for each survey area, I digitized the locations and boundaries of patches into a GIS layer. I calculated the

perimeter, area, and average elevation of each patch, and the distance to the nearest neighboring patch. I used GIS layers of trails, campsites, and roads throughout NOCA and calculated the nearest distance from each survey area and patch to a trail, campsite, and road. Using data from the habitat transects, I determined the percent cover for each cover type in each 1-m² plot by assigning the mean value of the corresponding cover range. For example, for a cover type with a cover range of 25-50%, I assigned an average cover within the plot of 38%. I calculated the average percent cover for each cover type across all six 1-m² plots and multiplied this by the patch area to get an area for each cover type. For patches having more than one transect, I divided the cover type area as determined from each transect by the number of transects, and then added the values together to get a weighted total area for each cover type within each patch. Finally, I calculated the proportion of cover for each cover type in each patch. I defined vegetation cover as that consisting of graminoid, forb, cushion plant, fern, bryophyte, lichen, shrub, or tree cover types.

I obtained daily snow pack snow water equivalent (SWE), maximum temperature, and precipitation data for 2008-2009 from nine NRCS SNOTEL stations (NRCS 2009) located in and around NOCA. The stations located west of the Cascade Crest and Picket Crest divides were the Marten Ridge, Middle Fork of the Nooksack, and Wells Creek stations (NRCS 2009). Those located between the two divides were the Beaver Pass, Hozomeen Camp, Swamp Creek, and Thunder Basin stations (NRCS 2009). Stations situated east of the divides were located at Park Creek Ridge and Rainy Pass (NRCS 2009). Because SWE data for the Hozomeen Camp station was incomplete, I did not include it for the snow modeling.

I defined six response variables from the climate data for each station. From the snow pack SWE data I calculated: (1) *SWEMAX*, the maximum value of SWE between October 1, 2008 and April 30, 2009, and (2) *MELTDATE*, the date of spring snowmelt when SWE = 0. From the temperature data for July 1 through August 31, 2009 I calculated: (1) *TMAX*, the average maximum daily temperature; (2) *DAYS70*, the number of days with a maximum daily temperature > 70°F, and (3) *DAYS80*, the number of days with a maximum daily temperature > 80°F. From the precipitation data I calculated *PRECIP*, the total accumulated precipitation between April 1 and June 30, 2009. For each station I defined four covariates: (1) *ELEV*, elevation; (2) *LAT*, latitude; (3) *LONG*, longitude, and (4) *DIVIDE*, a categorical variable denoting the station location relative to the divides (i.e., west, middle, east). For each response

variable I developed multiple regression models (Neter et al. 1996) consisting of all possible additive combinations of covariates and also included models containing $ELEV*LAT$ and $ELEV*LONG$ interactions. I used multiple regression techniques in R (R Development Core Team 2008) to fit models and estimate covariate coefficients. I calculated a corrected Akaike's Information Criterion (AIC_c) value for each model, and ranked and selected the top approximating models for each response variable using ΔAIC_c values (Burnham and Anderson 2002). I then used the top model for each response variable to estimate $SWEMAX$, $MELTDATE$, $TMAX$, $DAYS70$, $DAYS80$, and $PRECIP$ for each survey area and patch. More detail on model selection using ΔAIC_c values is provided in Appendix B.

2D.2. Factors Affecting Pika Abundance on the Survey Area Scale. I defined a response variable, $ABUNDANCE_{area}$, as the total number of pikas counted within each survey area. For areas in which multiple surveys were conducted, I used the maximum count. I defined six covariates based on all patches in each survey area to be used in the *a priori* modeling analysis: (1) $PERIMETER_{area}$, the sum of patch perimeters; (2) $ELEV_{area}$, the average elevation of patches; (3) $DISTCAMP_{area}$, the average distance to the nearest campsite from patches; (4) $TMAX_{area}$, the average maximum daily temperature for July and August; (5) $SWEMAX_{area}$, the average maximum SWE, and (6) $COVER_{area}$, the overall proportion of vegetation cover. I formulated a hypothesis for each covariate regarding its correlation with the response as follows.

1. Abundance would be positively correlated with $PERIMETER_{area}$ because pikas live and forage at the patch edge (McIntire and Hik 2005), and larger perimeters would result in increased resource availability, which may result in increased pika abundance.
2. Abundance would be positively correlated with $ELEV_{area}$ because higher elevations should be more beneficial to pika thermoregulation needs (MacArthur and Wang 1974) during summer than those at lower elevations because higher elevations experience lower overall summer temperatures. Further, high elevation meadows may have increased abundance of preferred forage (Dearing 1996), resulting in increased resource availability and greater abundance.
3. Abundance would be positively correlated with $DISTCAMP_{area}$ because use of campsites by people may result in nearby talus patches having no or few pikas owing to disturbance. Survey areas close to campsites may have lower overall abundance of pikas than those farther from camps.

4. Abundance would be negatively correlated with $TMAX_{area}$ because areas with higher average maximum daily temperatures may be less suited for pikas because of potential negative effects on survival and reproduction (Smith 1974a, 1974b, 1978).
5. Abundance would be positively correlated with $SWEMAX_{area}$ because higher elevations generally receive greater snowfall and higher SWE values may result in a deeper or more insulating snowpack, thereby reducing cold stress to pikas during winter.
6. Abundance would be positively correlated with $COVER_{area}$ because higher proportions of vegetation cover within the patch would result in increased foraging opportunities for pikas without having to leave the patch edge, thereby reducing predation risk and minimizing thermal stress during the warmest hours of the day. Based on similar rationale I predicted that abundance would be positively correlated with a $PERIMETER_{area} * COVER_{area}$ interaction.

Because elevation was used to develop the predictive $SWEMAX$ and $TMAX$ models, no interactions between elevation, snow, and temperature were evaluated.

I developed competing *a priori* hypotheses expressed as 15 negative binomial regression models (Zuur et al. 2009) consisting of additive combinations of covariate main effects and interactions. I calculated variance inflation factors (VIFs; Neter et al. 1996) while forming the model list to quantify multicollinearity among model covariates and interactions. Models containing covariates having a $VIF > 5$ were not included in the list and, because of this, $TMAX_{area}$ and $SWEMAX_{area}$ were not included together in models. I used negative binomial regression techniques in R (R Development Core Team 2008, Zuur et al. 2009) to fit models and estimate covariate coefficients. To allow comparisons of coefficients on a similar scale, each continuous covariate was centered and scaled prior to analysis by subtracting the midpoint and dividing by half of the range resulting in values between -1.0 and 1.0 (Bruggeman et al. 2006). I calculated an AIC_c value for each model, and ranked and selected the top approximating models using ΔAIC_c values (Burnham and Anderson 2002). Finally, I calculated Akaike weights (w) for each model to obtain a measure of model selection uncertainty (Burnham and Anderson 2002). Models having a $w \approx 0.0$ have little support based on the data available, while models having a $w \approx 1.0$ have a high amount of support from the data.

I defined nine covariates based on all patches in each survey area to be used in exploratory modeling analyses: (1) $AREA_{area}$, the sum of patch areas; (2) $DISTROAD_{area}$, the average distance to the nearest road from patches; (3) $DISTTRAIL_{area}$, the average distance to the

nearest trail from patches; (4) $DAYS70_{area}$, the average number of days with a maximum daily temperature $> 70^{\circ}F$; (5) $DAYS80_{area}$, the average number of days with a maximum daily temperature $> 80^{\circ}F$; (6) $MELTDATE_{area}$, the average date of spring snowmelt; (7) $PRECIP_{area}$, the average total accumulated precipitation; (8) $DIVIDE_{area}$, a categorical variable denoting the survey area location relative to the divides (i.e., west, middle, east), and (9) $FORAGECOVER_{area}$, the sum of proportions of cushion plant, forb, and graminoid cover types. Using the top approximating models with $\Delta AIC_c < 2$ from the *a priori* analysis, I substituted $AREA_{area}$ for $PERIMETER_{area}$, calculated a new AIC_c value, and compared the AIC_c values from the *a priori* and exploratory analyses. I separately added each of the remaining eight exploratory covariates to the top approximating *a priori* models, calculated new AIC_c values, and compared *a priori* and exploratory AIC_c values for each model.

2D.3. Factors Influencing Pika Abundance on the Talus Patch Scale. I defined a response variable, $ABUNDANCE_{patch}$, as the number of pikas counted in each patch. For patches in which multiple surveys were conducted, I used the maximum count. I defined 12 covariates based on each patch to be used in the *a priori* analysis: (1) $PERIMETER_{patch}$, the patch perimeter; (2) $ELEV_{patch}$, the patch elevation; (3) $ASPECT_{patch}$, a categorical variable denoting the predominant patch aspect (i.e., NW, N, NE, E, SE, S, SW, W); (4) $DISTPATCH_{patch}$, the distance to the nearest neighboring patch; (5) $DISTTRAIL_{patch}$, the distance from the patch to the nearest trail; (6) $COVER_{patch}$, the proportion of vegetation cover within the patch; (7) $DEPTH_{patch}$, the average maximum talus depth recorded in the patch; (8) $TEMPMAX$, the maximum temperature recorded at the talus surface during habitat data collection, and (9) $TEMPMIN$, the minimum temperature recorded beneath the talus surface. Because the maximum and minimum temperatures were recorded at a specific time, I defined $TEMPMAX_{time}$ and $TEMPMIN_{time}$, which corresponded to the time at which the maximum and minimum temperature were recorded, respectively. I also defined $TEMPDATE$ as the Julian date on which the temperature was recorded. I formulated a hypothesis for each covariate regarding its correlation with the patch abundance response variable as follows.

1. Abundance would be positively correlated with $PERIMETER_{patch}$, $ELEV_{patch}$, and $COVER_{patch}$ based on similar rationale to that for the survey area analysis,
2. Abundance would be higher in patches with northerly aspects (NW, N, NE) and lower in patches with southerly aspects (SW, S, SE) because south facing patches receive more direct

sunlight and have higher temperatures during summer, while northerly patches would generally experience the opposite.

3. Abundance would be negatively correlated with $DISTPATCH_{patch}$ because pikas would be more likely to disperse to and colonize nearby patches than those farther away (Moilanen et al. 1998).
4. Abundance would be positively correlated with $DISTTRAIL_{patch}$ because human presence on trails may result in pikas not colonizing certain patches owing to disturbance. Increased vigilance by pikas when monitoring trails for people and/or predators may result in decreased time foraging and stocking haypiles, which may ultimately negatively impact survival and recruitment.
5. Abundance would be positively correlated with $DEPTH_{patch}$ because patches with greater sub-surface depths may have cooler microclimates during summer that are beneficial to pika thermoregulation and provide more protection from predators.
6. Abundance would be negatively correlated with $TEMPMAX$ and $TEMPMIN$ because of the negative effects of higher temperatures on pika survival (Smith 1974b).

I made no hypotheses about the individual $TEMPMAX_{time}$, $TEMPMIN_{time}$, and $TEMPDATE$ covariates because they were to be used only in models that contained $TEMPMAX$ and/or $TEMPMIN$ to adjust for time and date effects on temperature measurements.

I developed competing *a priori* hypotheses expressed as 65 negative binomial regression models (Zuur et al. 2009) consisting of additive combinations of covariate main effects and interactions. I calculated VIFs while forming the model list to quantify multicollinearity among model covariates and interactions, and models containing covariates having a $VIF > 5$ were not included in the list. Because of multicollinearity $ELEV_{patch}$ and $TEMPMIN$ were not included together in any models. Models containing $TEMPMAX$ also included $TEMPMAX_{time}$, $TEMPDATE$, and $TEMPMAX*TEMPMAX_{time}$ and $TEMPMAX*TEMPDATE$ interactions because of the need to account for date and time effects on temperature. Likewise, models containing $TEMPMIN$ also included $TEMPMIN_{time}$, $TEMPDATE$, and $TEMPMIN*TEMPMIN_{time}$ and $TEMPMIN*TEMPDATE$ interactions. I used negative binomial regression techniques in R (R Development Core Team 2008, Zuur et al. 2009) to fit models and estimate covariate coefficients. Each continuous covariate was centered and scaled prior to analysis by subtracting the midpoint and dividing by half of the range (Bruggeman et al. 2006). I calculated an AIC_c

and w value for each model, and ranked and selected the top approximating models using ΔAIC_c values (Burnham and Anderson 2002).

I defined 11 covariates to be used in exploratory modeling analyses: (1) $AREA_{patch}$, the patch area; (2) $DISTROAD_{patch}$, the distance to the nearest road from the patch; (3) $DISTCAMP_{patch}$, the distance to the nearest camp from the patch; (4) $DAYS70_{patch}$, the number of days with a maximum daily temperature $> 70^\circ\text{F}$; (5) $DAYS80_{patch}$, the number of days with a maximum daily temperature $> 80^\circ\text{F}$; (6) $MELTDATE_{patch}$, the date of spring snowmelt; (7) $PRECIP_{patch}$, the total accumulated precipitation; (8) $DIVIDE_{patch}$, a categorical variable denoting the patch location relative to the divides; (9) $FORAGECOVER_{patch}$, the sum of proportion of cushion plant, forb, and graminoid cover types in the patch; (10) $TMAX_{patch}$, the average maximum daily temperature for July and August, and (11) $SWEMAX_{patch}$, the average maximum SWE. Using the top approximating models with $\Delta AIC_c < 2$ from the *a priori* analysis I substituted $AREA_{patch}$ for $PERIMETER_{patch}$, calculated a new AIC_c value, and compared the AIC_c values from the *a priori* and exploratory analyses. I separately added each of the remaining 10 exploratory covariates to the top approximating *a priori* models, calculated new AIC_c values, and compared *a priori* and exploratory AIC_c values for each model.

2D.4. Factors Influencing the Probability of Talus Patch Use. I assigned a binary response variable to each patch depending on whether pikas were detected (“1”) or not detected (“0”) during surveys. Patches in which pikas were not detected were not assumed to be unused by pikas; rather, these patches were considered to be available to pikas. For patches in which multiple surveys were conducted, I considered patches with a detection during any survey to be used by pikas. Because the spatial scale was the same as that for the patch abundance analysis, I used the same 12 covariates for the *a priori* patch use-availability analysis. My hypotheses regarding the correlation of each covariate with the response were the same as those for the patch abundance analysis. However, because a binary response was used and logistic regression techniques (Hosmer and Lemeshow 2000) were required, my predictions were with regard to the probability of patch use rather than patch abundance.

I developed competing *a priori* hypotheses expressed as 65 logistic regression models (Hosmer and Lemeshow 2000) consisting of additive combinations of covariate main effects and interactions. My model list was the same as that used for the patch abundance analysis. I used logistic regression techniques in R (R Development Core Team 2008) to fit models and estimate

covariate coefficients. Each continuous covariate was centered and scaled prior to analysis (Bruggeman et al. 2006). I calculated an AIC_c and w value for each model, and ranked and selected the top approximating models using ΔAIC_c values (Burnham and Anderson 2002). I used the same 11 covariates and methods as used for the patch abundance exploratory analysis for the patch use-availability exploratory analysis.

2D.5. Factors Affecting Detectability and Variability in Survey Area Abundance. Using data from the repeat surveys of eight survey areas, I defined a response variable, $COUNT_{area}$, as the number of pikas counted in each area during each survey. I defined four covariates for use in the analysis: (1) $SURVEYDATE_{area}$, the Julian date of the survey; (2) $VISIT_{area}$, a categorical variable denoting the survey number (i.e., 1, 2, 3); (3) $TEMP_{area}$, the average temperature at which locations were obtained or, if no pikas were found, the survey was conducted, and (4) $WEATHER_{area}$, a categorical variable denoting the predominant weather condition during the survey (i.e., cloudy, partly cloudy, mostly cloudy, rainy, sunny). I hypothesized that:

1. Count would be positively correlated with $SURVEYDATE_{area}$ because of the possibility that late season surveys may account for juveniles that emerged from the talus and dispersed after early season surveys were completed.
2. Counts would be higher during second and third surveys based on the same rationale as (1), and because surveyors would have experience and knowledge of the area and pika locations from the first survey.
3. Count would be negatively correlated with $TEMP_{area}$ because pikas would be less detectable as temperature increases because pikas are more likely to remain under the talus in cooler microclimates during periods of high surface temperatures (Smith 1974b).
4. Based on similar reasoning to (3), counts would be higher in cloudy and partly cloudy weather conditions because of less exposure to direct sunlight, thereby reducing daytime temperatures and making surface conditions more favorable to pikas.

I developed competing *a priori* hypotheses expressed as 14 mixed-effects Poisson regression models (Zuur et al. 2009) consisting of additive combinations of covariate main effects. Models containing covariates having a $VIF > 5$ were not included in the model list. Because the count data consisted of repeated measurements on each of the eight survey areas, I defined $SURVEYAREA$, a categorical covariate denoting each survey area number, as a random intercept effect in each model. I used mixed-effects Poisson regression techniques in R (R

Development Core Team 2008, Zuur et al. 2009) to fit models and estimate covariate coefficients. Each continuous covariate was centered and scaled prior to analysis (Bruggeman et al. 2006). I calculated an AIC_c and w value for each model, and ranked and selected the top approximating models using ΔAIC_c values (Burnham and Anderson 2002).

To address variability in counts, I defined a second response variable, SE_{area} , as the standard error of the counts for each survey area. I defined five covariates to be used in the analysis: (1) $AVGCOUNT_{area}$, the average of all counts for each survey area; (2) $ELEV_{area}$, the average elevation of patches in the survey area; (3) $AREA_{area}$, the sum of patch areas; (4) $ROCKCOVER_{area}$, the sum of proportions of talus, large rock, and small rock cover for all patches in survey area, and (5) $DEPTH_{area}$, the average maximum talus depth recorded for all patches in the area. I hypothesized that:

1. SE_{area} would be positively correlated with $AVGCOUNT_{area}$ because higher counts would likely result in more variability about the mean.
2. SE_{area} would be positively correlated with $ELEV_{area}$ because pika abundance is likely to be greater at higher elevations because of lower temperatures and availability of preferred forage.
3. SE_{area} would be positively correlated with $AREA_{area}$ and $ROCKCOVER_{area}$ because pikas may be less detectable in large patches and in areas with high proportions of rock cover compared to vegetation.
4. Based on similar rationale as (3), SE_{area} would be positively correlated with $DEPTH_{area}$ because patches with greater talus depths offer more sub-surface area for protection, thereby making pikas less likely to alarm call and less detectable.

I developed competing *a priori* hypotheses expressed as eight mixed-effects regression models (Pinheiro and Bates 2000, Zuur et al. 2009) consisting of additive combinations of covariate main effects. Models containing covariates having a $VIF > 5$ were not included in the model list and, as a result of multicollinearity, $AVGCOUNT_{area}$ could not be combined with three and four other covariates in the same model. I defined $SURVEYAREA$ as a random intercept effect in each model because I wanted to be able to make inference to all survey areas and not just the eight that were surveyed multiple times. I used mixed-effects regression techniques in R (Pinheiro and Bates 2000, R Development Core Team 2008) to fit models and estimate covariate coefficients. Each continuous covariate was centered and scaled prior to analysis (Bruggeman et

al. 2006). I calculated an AIC_c and w value for each model, and ranked and selected the top approximating models using ΔAIC_c values (Burnham and Anderson 2002).

2D.6. Factors Affecting Temperature Change Beneath the Talus Surface. Using temperature data gathered as part of habitat data collection, I defined a response variable, ΔT , as the temperature change between the talus surface and sub-surface. For plots in which the temperature was lower beneath the talus surface than at the surface, ΔT was negative. I defined six covariates for use in the modeling analysis: (1) *DATE*, the Julian date on which the temperature was recorded; (2) *ASPECT*, a categorical variable denoting the predominant aspect of the transect aspect (i.e., NW, N, NE, E, SE, S, SW, W); (3) *TALUSDEPTH*, the depth beneath the talus at which the temperature was recorded; (4) *TIME*, the time of day at which the temperature was recorded; (5) *SURFACETEMP*, the temperature at the talus surface, and (6) *ELEV*, the elevation of the transect. I hypothesized that:

1. ΔT would be negatively correlated with *DATE* because the difference between surface and sub-surface temperatures would increase as the summer progresses and air temperatures increase.
2. ΔT would be positively correlated for patches with southerly aspects (i.e., south; southwest; southeast) and negatively correlated for patches with northerly aspects (i.e., north; northwest; northeast) because of the increased exposure to direct sunlight and increased surface temperatures in south-facing patches.
3. ΔT would be negatively correlated with *TALUSDEPTH* because of the potential for microclimates at greater depths to maintain cool temperatures even when surface temperatures rise.
4. ΔT would be negatively correlated with *SURFACETEMP* because the temperature drop would increase as surface temperatures rise and sub-surface microclimates remain cool.
5. ΔT would be positively correlated with *TIME* because surface temperatures would increase from morning through afternoon.
6. ΔT would be negatively correlated with *ELEV* because higher elevations are more likely to experience cooler night temperatures and areas beneath the talus may retain these cooler temperatures throughout the day even as surface temperatures increase.

I developed competing *a priori* hypotheses expressed as 32 mixed-effects regression models (Pinheiro and Bates 2000, Zuur et al. 2009) consisting of additive combinations of

covariate main effects. Models containing covariates having a VIF > 5 were removed from the list. Because the data consisted of temperature measurements along transects in each patch, I defined *TRANSECT* as a random intercept effect in each model. I used mixed-effects regression techniques in R (Pinheiro and Bates 2000, R Development Core Team 2008) to fit models and estimate covariate coefficients. Each continuous covariate was centered and scaled prior to analysis (Bruggeman et al. 2006). I calculated an AIC_c and w value for each model, and ranked and selected the top approximating models using ΔAIC_c values (Burnham and Anderson 2002).

Because the temperature varies with time of day and date, I conducted exploratory analyses to examine the effect of quadratic forms of *TIME* and *DATE* in the top approximating *a priori* models. I separately added $TIME^2$ and $DATE^2$ into the top approximating models, calculated AIC_c values for each model, and compared the new AIC_c value to that obtained from the *a priori* analysis. I also added both $TIME^2$ and $DATE^2$ into the top approximating models, and compared AIC_c values between *a priori* and exploratory analyses.

2D.7. Power Analyses Examining Changes in Mean Pika Abundance. I calculated the mean and standard deviation (SD) for the abundance data from all 30 survey areas. I used these statistics to conduct a power analysis (Peterman 1990) in R (R Development Core Team 2008) to examine how varying the effect size from 0.1 to 0.9 influences the power to detect both an annual change (i.e., increase or decrease) and decline in mean pika abundance at $\alpha = 0.05$. I also used the mean and SD to determine how increasing the sample size beyond 30 survey areas increases the ability to detect a decline in mean abundance at a power of 0.8.

I also conducted power analyses for survey areas within the five elevation strata (i.e., ≤ 913 m; 914-1,218 m; 1,219-1,523 m; 1,524-1,827 m; $\geq 1,828$ m). For survey areas within each elevation strata, I calculated the mean abundance and SD. I then examined how varying effect size influences the power to detect both an annual change and decline in mean pika abundance in each stratum at $\alpha = 0.05$. I also examined how increasing the sample size of survey areas within each stratum increases the power to detect a decline in mean abundance.

2D.8. Additional Analyses. Based on the five elevation strata (i.e., ≤ 913 m; 914-1,218 m; 1,219-1,523 m; 1,524-1,827 m; $\geq 1,828$ m), I assigned each survey area and patch to an elevation category and calculated the density of pikas per survey area and patch. I calculated survey area densities as the total number of pikas counted in the survey area divided by the total patch area for all patches in the area. I calculated patch densities as the number of pikas counted

in the patch divided by the patch area. I then used analysis of variance (ANOVA) techniques (Neter et al. 1996) to examine how pika densities in survey areas and patches are related to elevation.

I used stratified random sampling equations (Thompson 2002) to estimate the mean population size and variance for each elevation stratum, and for the overall population. The number and size of patches varies among survey areas, so the assumption was required that the sample of 30 survey areas was representative of all survey areas in the sampling universe. Because the sample sizes of survey areas within some of the 15 strata were small, I combined survey areas among divide locations into one of the five elevation strata.

Using data obtained from the repeat surveys in eight survey areas, I calculated the standard error of counts for each area and for each patch within the areas. I then built regression models to examine how the standard error for survey area counts is correlated with the number of pikas counted per area per survey, and how the standard error for patch counts is correlated with the number of pikas counted per patch per survey. I used regression techniques in R (R Development Core Team 2008) to fit models and estimate parameter coefficients.

3. RESULTS

3A. Pika Abundance, Distribution, and Population Estimates

Between June 21 and September 27, 2009, surveyors found active pika presence in 27 of 30 (90%) survey areas (Figure 2) with pika abundance per survey area ranging from 0 to 101 individuals (mean = 23.6; SE = 4.6; Appendix A, Table A2). Within the 30 survey areas surveyors counted a total of 707 pikas in 115 talus patches, of which 85 (74%) had active pika presence. Of the remaining 30 patches, surveyors found old pika sign in 14 (47%) patches; 16 patches had no new or old pika sign. Of the 707 locations, 47.7% were visual sightings, 44.7% were pika vocalizations, and 7.7% were active haypiles. Pika abundance per patch ranged from 0 to 65 individuals (mean = 6.2; SE = 1.0) and pikas were found in patches ranging in elevation between 351 and 2,130 m (mean = 1,457; SE = 44; Appendix A, Table A3), which spanned the entire range of elevations for patches surveyed. The elevation of patches in which no active pika presence was found ranged from 373 to 1,708 m (mean = 1,335; SE = 126). Within the defined sampling universe (< 3 km from a trail or road), the overall pika population estimate for NOCA

within the defined sampling universe was 22,279 pikas (95% CI: 6,706, 37,852). Population estimates for each of the five elevation strata are provided in Table 1.

The number of patches that were surveyed per survey area ranged from 1 to 15 (mean = 3.8; SE = 0.6; Appendix A, Table A2). Talus patch area ranged from 0.003 to 41.9 ha (mean = 2.3; SE = 0.6) and the total area of patches per survey area ranged from 0.35 to 43.8 ha (mean = 8.7; SE = 2.1). Talus patch perimeter varied between 0.22 and 9.5 km (mean = 0.98; SE = 0.15) and was positively correlated with the mean elevation of each survey area (estimate = 0.78; SE = 0.33; $R^2 = 0.05$; $P = 0.02$). The total patch perimeter per survey area ranged from 0.46 and 10.5 km (mean = 3.66; SE = 0.55) and was positively correlated with the mean elevation of each survey area (estimate = 3.4; SE = 0.9; $R^2 = 0.35$; $P = 0.001$). The density of pikas per talus patch ranged from 0 to 69.2 pikas/ha (mean = 10.7; SE = 1.5; Figure 3a) while the density of pikas per total patch area in survey areas varied between 0 and 25.9 pikas/ha (mean = 5.0; SE = 1.1; Figure 3b). Pika density per patch varied significantly with elevation stratum (ANOVA: $F_{4,97} = 4.68$, $P = 0.002$), as patches at middle elevations (914 to 1,828 m) supported higher densities than patches at low (< 914 m) and high ($\geq 1,828$ m) elevations (Figure 4a). On the survey area scale, pika density per total patch area varied significantly with elevation (ANOVA: $F_{4,23} = 6.49$, $P = 0.001$), with middle elevation areas (1,219-1,523 m) supporting higher pika densities than low and high elevation areas (Figure 4b).

Surveyors conducted three repeat surveys in five survey areas containing a total of 11 talus patches and two repeat surveys in three areas containing seven patches (Figure 5). Of the five areas surveyed three times, the number of pikas counted in three of the areas increased or remained the same with each successive visit (Figure 5a). Similarly, surveyors counted more pikas in all three areas that were surveyed two times (Figure 5a). The average percent change in the number of pikas counted was 19.1% (SE = 15.6) between the first and second survey, and 28.8% (SE = 75.2) between the first and third survey. At both the survey area and patch scales, the standard error of the count was positively correlated with the number of pikas counted (Figure 6). For the survey area scale the correlation was significant ($P < 0.001$) with a coefficient for the number of pikas counted of 0.134 (SE = 0.020) and intercept of 0.986 (SE = 0.374), and the model had an adjusted R^2 value of 0.69 (Figure 6a). For the patch scale the correlation was also significant ($P < 0.001$) with a coefficient of 0.119 (SE = 0.009) and intercept of 0.665 (SE = 0.105), and an adjusted R^2 of 0.81 (Figure 6b).

3B. Talus Patch Habitat and Temperature Characteristics

Surveyors completed 196 25-m transects encompassing 1,176 1-m² plots in 103 of the 115 patches to record vegetation cover and talus surface and sub-surface temperatures. Habitat data was not recorded in 12 patches owing to time constraints during the survey. Surveyors recorded talus cover in 1,062 1-m² plots with an average cover per plot of 53.8% (SE = 1.0) and talus depth ranging from 0 to 1.90 m (mean = 0.45; SE = 0.01). Talus surface temperatures varied between 43.4°F, recorded at 18:36 on September 20, and 108.5°F, recorded at 13:26 on July 4 (mean = 71.0; SE = 0.4; Figure 7a). Sub-surface talus temperatures ranged from 35.3°F, recorded at 9:44 on July 10 at a depth of 0.43 m, to 93.2°F, recorded at 17:08 on July 4 at a depth of 0.41 m (mean = 58.4; SE = 0.3; Figure 7b). The mean temperature change between the talus surface and sub-surface was -12.9°F (SE = 0.3) with the largest drop of -44.8°F recorded at 13:52 on July 2 at a depth of 1.0 m (Figures 8a, 8b). The largest increase of 7.3°F was recorded at 17:11 on August 24 at a depth of 0.1 m (Figures 8a, 8b). The temperature gradient (i.e., temperature change per meter below the surface) varied between -6.43 and 1.83°F/m (mean = -0.75; SE = 0.02), with variability in the gradient decreasing with depth (Figure 9).

For vegetation cover types, the overall frequency of occurrence in plots ranged from 0.02 for trees to 0.64 for bryophytes (Figure 10a) while the mean average percent cover per plot varied between 4.4% (SE = 0.3) for lichens and 28.7% (SE = 1.9) for shrubs (Figure 10b). Surveyors recorded large and small rocks in 34.9% and 47.2% of plots, respectively. The mean average percent cover of large rocks per plot was 39.8% (SE = 1.5) while that for small rocks was 11.7% (SE = 0.7). Additional prominent cover types in plots included woody debris, which surveyors recorded in 31.8% of plots, bare ground (13.2%), and forest litter (10.3%). The mean average percent cover per plot was 8.0% (SE = 0.7) for woody debris, 14.1% (SE = 1.3) for bare ground, and 9.1% (SE = 1.3) for forest litter.

The frequency of occurrence of vegetation cover types in plots varied with elevation (Figure 11a). Bryophytes and lichens occurred most frequently in plots at low and middle elevations, while cushion plants, forbs, graminoids, and shrubs were documented more often at higher elevations (Figure 11a). The mean average percent cover varied with elevation for some vegetation types (Figure 11). Average bryophyte cover decreased with elevation with significant declines occurring between plots at < 914 m and those at 914 to 1,523 m, and between plots at

914 to 1,523 m and those at > 1,524 m (Figure 11b). For cushion plants, the mean average percent cover increased with elevation, although confidence intervals overlapped among elevation ranges (Figure 11b). Average fern cover decreased with elevation, with a significant decrease occurring between plots at 1,219 to 1,523 m and those at 1,524 to 1,827 m (Figure 11c). For forbs, mean average percent cover in plots was greater at elevations > 1,827 m compared to plots at lower elevations; however, confidence intervals overlapped among elevation ranges (Figure 11c). Average graminoid cover was significantly lower in plots at elevations > 1,827 m compared to those at 1,219 to 1,827 m (Figure 11d). The average cover of lichens in plots between high and low elevation plots (Figure 11d), while shrub cover was significantly lower in plots at elevations at 914 to 1,218 m compared to those > 1,218 m (Figure 11d).

3C. Statistical and Modeling Analyses

3C.1. Climate Covariate Models. The top approximating model for the *SWEMAX* modeling had a $w = 0.684$, adjusted $R^2 = 0.45$, and included a significant *LONG* covariate (estimate = -30.42; SE = 11.72). For the *MELTDATE* modeling the top model had a $w = 0.345$, adjusted $R^2 = 0.60$, and included a significant *LONG* covariate (estimate = -22.66; SE = 7.73) and an *ELEV* covariate (estimate = 0.016; SE = 0.007). The top model for *TMAX* had a $w = 0.580$, adjusted $R^2 = 0.97$, and included significant *LONG* (estimate = 19.51; SE = 5.37) and *ELEV* (estimate = -0.404; SE = 0.147) covariates, and a significant *ELEV*LONG* interaction (estimate = -0.003; SE = 0.001). The top model for the *DAYS70* modeling had a $w = 0.805$, adjusted $R^2 = 0.93$, and included significant *LONG* (estimate = 11.47; SE = 2.04) and *ELEV* (estimate = -0.008; SE = 0.001) covariates. For the *DAYS80* modeling the top model had a $w = 0.341$, adjusted $R^2 = 0.92$, and included significant *LONG* (estimate = 53.37; SE = 17.55) and *ELEV* (estimate = -1.32; SE = 0.48) covariates, and a significant *ELEV*LONG* interaction (estimate = -0.011; SE = 0.004). Finally, the top model for the *PRECIP* modeling had a $w = 0.529$, adjusted $R^2 = 0.74$, and included a significant *LONG* covariate (estimate = -11.13; SE = 2.26).

3C.2. Factors Affecting Pika Abundance on the Survey Area Scale. There were three models with $\Delta AIC_c < 2$ for the *a priori* analysis with the top approximating model having a $w = 0.296$ and an explained deviance (Zuur et al. 2009) of 49.0%. All three models contained significant, positive *PERIMETER*_{area} (Figure 12a) and *ELEV*_{area} (Figure 12b) covariates with

coefficient confidence intervals that did not overlap zero. The model averaged coefficient (Burnham and Anderson 2002) for $PERIMETER_{area}$ was 0.741 (SE = 0.310) and for $ELEV_{area}$ was 0.967 (SE = 0.412). The second ($\Delta AIC_c = 1.48$, $w = 0.141$) and third best models ($\Delta AIC_c = 1.55$, $w = 0.137$) also included $SWEMAX_{area}$ and $TMAX_{area}$, respectively. However, both covariates had confidence intervals that slightly overlapped zero with the coefficient for $SWEMAX_{area}$ being 0.329 (SE = 0.255) and for $TMAX_{area}$, -0.437 (SE = 0.344). Appendix B provides more detail on how to interpret these model results.

The exploratory analyses yielded no improvement (i.e., lower AIC_c values) over results from the *a priori* analysis. Substituting $AREA_{area}$ for $PERIMETER_{area}$ increased *a priori* AIC_c values by as much as 4.5 in the top models, which suggests that patch perimeter is a better covariate than area in relation to pika abundance. Separately adding $DISTROAD_{area}$, $DISTTRAIL_{area}$, $MELTDATE_{area}$, $PRECIP_{area}$, $DIVIDE_{area}$, and $FORAGECOVER_{area}$ to the top models all resulted in increases in *a priori* AIC_c values. Addition of $DAYS70_{area}$ or $DAYS80_{area}$ lowered AIC_c values for the second and third best models. However, because of multicollinearity between climate covariates, the covariate coefficients were not interpretable.

3C.3. Factors Influencing Pika Abundance on the Talus Patch Scale. Three models had $\Delta AIC_c < 2$ for the *a priori* analysis and all contained significant, positive $PERIMETER_{patch}$ (Figure 13a) and negative $TEMPMIN$ (Figure 13b) covariates with coefficient confidence intervals not spanning zero (Table 2). The top model had a $w = 0.218$, an explained deviance (Zuur et al. 2009) of 54.0%, and also contained positive $TEMPMAX$ and $TEMPDATE$ covariates with confidence intervals not overlapping zero (Table 2). Additionally, the top model contained a negative $TEMPMAX*TEMPDATE$ interaction with confidence intervals that slightly spanned zero (Table 2). The second best model ($\Delta AIC_c = 1.02$, $w = 0.131$) contained a significant, positive $TEMPMIN_{time}$ covariate and a positive $TEMPDATE$ covariate that had confidence intervals slightly overlapping zero (Table 2). The third best model ($\Delta AIC_c = 1.73$, $w = 0.092$) included positive $TEMPMAX$ and $TEMPDATE$ covariates with confidence intervals not spanning zero, and a negative $TEMPMAX*TEMPDATE$ interaction with confidence intervals slightly overlapping zero (Table 2). Exploratory analyses resulted in no improvement compared to the *a priori* analysis. Substituting $AREA_{patch}$ for $PERIMETER_{patch}$ increased *a priori* AIC_c values as did separately adding $DISTROAD_{patch}$, $DISTCAMP_{patch}$, $DAYS70_{patch}$, $DAYS80_{patch}$, $MELTDATE_{patch}$, $PRECIP_{patch}$, $DIVIDE_{patch}$, $FORAGECOVER_{patch}$, $TMAX_{patch}$, and $SWEMAX_{patch}$.

3C.4. Factors Influencing the Probability of Talus Patch Use. There were eight models with $\Delta AIC_c < 2$ for the *a priori* analysis with the top approximating model having $w = 0.102$ (Table 3) and an explained deviance (Zuur et al. 2009) of 37%. The only covariate that was significant in all top models was *TEMPDATE*, which was positively correlated with the probability of patch use. Other significant, positive covariates contained in some of the top eight models were *TEMPMAX*, *PERIMETER*_{patch}, northeast *ASPECT*_{patch}, and a *TEMPMIN*TEMPDATE* interaction. The two significant, negative covariates contained in some of the top models were *TEMPMIN* and a *TEMPMAX*TEMPDATE* interaction. For model averaged coefficient estimates (Burnham and Anderson 2002) only *TEMPMAX*, *TEMPDATE*, and a northeast *ASPECT*_{patch} had confidence intervals that did not span zero (Table 4). Confidence intervals slightly spanned zero for model averaged coefficient estimates for *PERIMETER*_{patch}, *DISTTRAIL*_{patch}, and *DEPTH*_{patch} covariates, and *TEMPMIN*TEMPDATE* and *TEMPMAX*TEMPDATE* interactions (Table 4).

Exploratory analyses provided some improvements to the top *a priori* models. Addition of *DISTCAMP*_{patch} and *DISTROAD*_{patch} lowered AIC_c values for three and one of the eight top models, respectively. The largest improvements came when adding *SWEMAX*_{patch}, which lowered AIC_c values for six models, and *FORAGECOVER*_{patch}, which improved all eight models. I then conducted further exploratory analyses to determine the combinations of *SWEMAX*_{patch}, *FORAGECOVER*_{patch}, *DISTCAMP*_{patch}, and *DISTROAD*_{patch} that provided the lowest AIC_c values for the eight models, and then ranked and selected the top exploratory models using ΔAIC_c values. The smallest and largest decreases in AIC_c values compared to *a priori* model values were 1.00 and 6.53, respectively. There were two top exploratory models with $\Delta AIC_c < 2$ with the second best model having a $\Delta AIC_c = 0.58$. The top exploratory model contained significant, positive *DISTTRAIL*_{patch} and *TEMPDATE* covariates, and a significant, negative *FORAGECOVER*_{patch} covariate (Table 5). The second best exploratory model contained a significant, positive *DISTTRAIL*_{patch} covariate and a positive *SWEMAX*_{patch} covariate that had coefficient confidence intervals that slightly spanned zero (Table 5).

3C.5. Factors Affecting Detectability and Variability in Survey Area Abundance. There was one top approximating model with $\Delta AIC_c < 2$ for the count analysis. The top model had a $w = 0.602$ and included a significant, positive *SURVEYDATE*_{area} covariate (estimate = 0.414; SE = 0.135; Figure 14a) with coefficient confidence intervals not spanning zero. The random

SURVEYAREA intercept effect had a variance of 1.20. The top model had a relative likelihood of 4.4 compared to the second best model ($\Delta AIC_c = 2.96$, $w = 0.137$) that contained a significant, negative *TEMP_{area}* covariate (estimate = -0.238; SE = 0.096), indicating the top model was highly supported by the data.

There also was only one top approximating model with $\Delta AIC_c < 2$ for the standard error analysis that was highly supported by the data with a $w = 0.886$ and a relative likelihood of 23.8 compared to the second best model ($\Delta AIC_c = 6.34$, $w = 0.037$). The top model contained a positive, significant *AVGCOUNT_{area}* covariate (estimate = 3.08; SE = 0.72; Figure 14b) with confidence intervals that did not overlap zero. The random intercept effect, *SURVEYAREA*, had a variance of 1.65 while the residual variance for the model was 0.23.

3C.6. Factors Affecting Temperature Change Beneath the Talus Surface. There was one top approximating model with $\Delta AIC_c < 2$ that was highly supported by the data with a $w = 0.960$ and a relative likelihood of 24.0 compared to the second best model ($\Delta AIC_c = 6.36$, $w = 0.039$). The top model contained a significant, positive *TIME* covariate (estimate = 1.95; SE = 0.73; Figure 6b) with coefficient confidence intervals not overlapping zero. Also included in the model were significant, negative *SURFACETEMP* (estimate = -21.21; SE = 0.80; Figure 15a), *DATE* (estimate = -2.73; SE = 0.62; Figure 15b), *TALUSDEPTH* (estimate = -4.24; SE = 0.32; Figure 6a), and *ELEV* (estimate = -3.32; SE = 0.80) covariates. Additionally, northeast (estimate = -2.75; SE = 1.40), northwest (estimate = -4.49; SE = 1.76), and southwest (estimate = -2.87; SE = 1.45) *ASPECT* covariates were significant, negative covariates with confidence intervals not spanning zero. The north *ASPECT* covariate was also negative, but had confidence intervals that slightly overlapped zero. The random intercept effect, *TRANSECT*, in the top model had a variance of 20.53 while the residual variance was 18.93.

For the exploratory analyses, adding *TIME*² to the top model lowered the AIC_c value by 5.66 while adding *DATE*² lowered the AIC_c value by 1.41. The largest improvement in AIC_c came from adding both *TIME*² and *DATE*² to the top model, which decreased the value by 7.11. This best exploratory model contained positive, significant *TIME* (estimate = 1.79; SE = 0.72) and *TIME*² (estimate = 3.34; SE = 1.48) covariates, and a negative, significant *DATE* covariate (estimate = -2.57; SE = 0.63) with confidence intervals not spanning zero. The *DATE*² covariate was negative, but did have confidence intervals that overlapped zero (estimate = -1.34; SE = 1.19). Other significant covariates and their corresponding coefficient estimates were similar

between the top *a priori* model and best exploratory model except for *ASPECT*. Northeast and southwest aspects had confidence intervals that spanned zero in the exploratory model, although the northwest aspect remained a significant, negative effect (estimate = -3.73; SE = 1.77).

3C.7. Power Analyses Examining Changes in Mean Pika Abundance. The mean abundance for all 30 survey areas was 23.6 pikas with a SD = 25.4. The power to detect a change or decline in mean pika abundance increased with the smallest detectable effect size, which corresponds to the smallest detectable percent change in population size (Figure 16a). For an annual decline in mean abundance at a power of 0.8 an effect size of 0.46 is detectable, which corresponds to a 50% decrease from 23.6 to 11.8 pikas. For an annual change in mean abundance at a power of 0.8 an effect size of 0.53 is detectable, which corresponds to a 57% decrease from 23.6 to 10.1 pikas or an increase to 37.0 pikas. Increasing the sample size of survey areas to > 30 would increase the ability to detect smaller effect sizes and population declines, with declines of < 43% and < 32% detectable at sample sizes of 40 and 70 survey areas, respectively (Figure 16b).

The mean abundance, SD, and sample size (*n*) for each elevation strata were:

1. Mean = 3.8, SD = 4.2, and *n* = 5 for survey areas \leq 913 m.
2. Mean = 5.8, SD = 8.0, and *n* = 5 for survey areas between 914 and 1,218 m.
3. Mean = 24.9, SD = 16.7, and *n* = 7 for survey areas between 1,219 and 1,523 m.
4. Mean = 35.6, SD = 28.5, and *n* = 9 for survey areas between 1,524 and 1,827 m.
5. Mean = 41.3, SD = 36.8, and *n* = 4 for survey areas \geq 1,828 m.

In part because of the small sample sizes in the \leq 913 m, 914 to 1,218 m, and \geq 1,828 m strata, the power to detect a > 96% decline in mean population size within each strata never was > 0.52 (Figure 17a). The 1,219 to 1,523 m and 1,524 to 1,827 m strata had large enough sample sizes and low enough CVs to detect a meaningful decline in mean population size. For the 1,219 to 1,523 m stratum an effect size of 1.07 can be detected at a power of 0.8, which corresponds to a 72% decline in mean population size for that stratum (Figure 17a). For the 1,524 to 1,827 m stratum an effect size of 0.91 is detectable at a power of 0.8, which equates to a 73% decrease in mean population size (Figure 17a). Similarly, the power to detect an increase or decrease in mean population size within each stratum was < 0.34 for the \leq 913 m, 914 to 1,218 m, and \geq 1,828 m strata (Figure 17b). For the 1,219 to 1,523 m stratum an effect size of 1.3 can be detected at a power of 0.8, which equals an 86% increase or decrease in mean population size

(Figure 17b). For the 1,524 to 1,827 m stratum an effect size of 1.07 is detectable at a power of 0.8, which corresponds to an 85% increase or decrease in mean population size (Figure 17b). To detect at least an 80% decline in mean population size within each strata, the sample size must be increased to > 12 areas for the ≤ 913 m stratum, > 19 areas for the 914 to 1,218 m stratum, and > 9 areas for the $\geq 1,828$ m stratum (Figure 18). A 50% decline in mean population size is detectable for the 1,219 to 1,523 m stratum with a sample size of > 12 areas, and for the 1,524 to 1,827 m stratum with > 17 areas (Figure 18).

4. DISCUSSION

4A. *Elevation Influences on Pika Abundance and Density*

Pika abundance on large and small scales in the North Cascades National Park Service Complex was influenced by multiple climate and habitat factors. On large scales, total pika abundance in survey areas was positively correlated with elevation, as predicted. This suggests higher elevation survey areas supported more pikas, which may be the result of interacting factors directly or indirectly affected by elevation. First, higher elevations experience lower maximum and minimum temperatures than lower elevations, thereby providing beneficial conditions during summer for pikas to minimize thermal stress. One of the top models included average maximum summer temperature, which was negatively correlated with abundance, although its coefficient confidence intervals slightly spanned zero, indicating the covariate contributed to fitting the model despite not being statistically significant. Beever et al. (2003) found that persistence of pika populations in the Great Basin was positively affected by increasing elevation and the maximum elevation of available talus, suggesting that high elevation talus patches offered a refuge to which pikas could move if temperatures at lower elevations increased beyond critical limits. Second, higher elevations may support more preferred vegetation types for pika foraging. While pikas are considered generalist herbivores and will graze and hay a wide variety of plant species (Dearing 1996, Richardson 2010, J. Bruggeman *personal observation*), they may preferentially select plants at different stages of growth because of water content and species dependent on nitrogen content (Morrison et al. 2004, Morrison and Hik 2008b). The vegetation cover type data collected for this study documented an increased frequency of occurrence of cushion plants and graminoids at higher elevations. Bryophytes and lichens were also observed less frequently at higher compared to lower elevations. Third, higher

elevations may experience greater snowfall, which provides insulating thermal cover over talus during winter and reduces the likelihood of pika mortality from exposure. A top approximating model did include maximum snow pack snow water equivalent, which is related to snow depth but also accounts for water content in the snow, although its coefficient confidence intervals slightly overlapped zero. Warmer winter temperatures at lower elevations may contribute to freezing rain or repeated freezing and thawing events that makes vegetation unavailable to foraging pikas because of ice and crusted snow pack, and may reduce the insulating value of snow pack (Smith et al. 2004, Morrison and Hik 2007).

While total abundance increased with elevation, pikas were present at low elevations and widely distributed throughout the North Cascades National Park Service Complex. Surveyors documented pikas at elevations as low as 351 m and of the 85 patches in which pikas were detected, 15 were below 1,219 m (4,000 ft). Additionally, only 12 of 30 patches in which pikas were not detected were below 1,219 m. Despite finding pikas at low elevations, the total abundance in these survey areas was low with an average count for areas below 1,219 m of 7.5 pikas (SE = 2.9). Low elevation pika populations at lower latitudes have been documented elsewhere, notably in Nevada (Beever et al. 2008) and Oregon (Simpson 2009), although these populations may be vulnerable to extirpation. The density of pikas in both survey areas and individual patches was also significantly lower at lower elevations compared to middle elevations, suggesting resource availability and vegetation quality increases with elevation. This is supported by habitat data and field observations that documented patch vegetation consisting of predominantly bryophytes and lichens at lower elevations. Low elevation pika populations appear to be occupying habitats of low to marginal quality at relatively low densities. Despite the trend in increasing pika density from low to middle elevations, pika density in survey areas and patches at high elevations ($\geq 1,828$ m) was significantly lower than at middle elevations. While higher elevations may experience lower summer temperatures and greater snowfall that is advantageous to pika survival under talus during winter, they may also have later dates of snowmelt that result in shortened growing seasons and delayed emergence of high quality vegetation. These time and resource restrictions on pika foraging during summer may result in a limited opportunity for grazing to meet summer energy needs and haying to stock vegetation for winter, thereby leading to lower survival rates or lower densities because of limited resource availability (Smith 1978). For example, Kreuzer and Huntly (2003) documented patches with

later snowmelt had birth rates negatively correlated with the date of snowmelt and acted as population sinks that supported pika populations mainly through immigration from higher quality, earlier melting patches. Also, Morrison and Hik (2007) found that adult survival was positively correlated with the Pacific Decadal Oscillation that, in turn, was negatively correlated with the timing of spring snowmelt.

4B. Temperature Influences on Pika Abundance

Temperatures at and below the talus surface influenced pika abundance in patches. As expected, abundance was negatively correlated with the minimum temperature recorded beneath the talus surface, suggesting as sub-surface temperatures increase, pika abundance decreases. Contrary to my hypothesis, abundance was positively correlated with the maximum temperature recorded at the talus surface. However, the effect of maximum temperature was abated by an interaction between the maximum temperature and date, which was negatively correlated with abundance and had coefficient confidence intervals that only slightly overlapped zero. The combination of the surface temperature positive main effect and negative interaction suggests that pika abundance in patches increased with temperature only to a certain point, and further increases in temperature resulted in decreased abundance. Pikas experience thermal stress at higher temperatures because of their thick fur and may die when exposed to temperatures above 77°F for several hours (Smith 1974b). At temperatures ranging from 37 to 81°F, MacArthur and Wang (1974) documented a negative correlation between the amount of time pikas spent at the talus surface and the surface temperature. Higher surface temperatures act to regulate the duration and intensity of pika surface activities, with pikas alternating between short periods on the surface and longer intervals beneath the talus to take advantage of cool, sub-surface microclimates. In patches where temperatures are regularly high during daytime hours in summer months, it is expected that pika abundance would be limited because of restrictions on the amount of time pikas could spend grazing and haying to meet summer and winter resource and energy needs. The lower abundance may be attributed to lower seasonal or annual survival rates, or pikas establishing territories in patches with more favorable climate conditions. The effects of sub-surface temperatures on pikas may be just as, if not more, critical than those of surface temperatures. Patches with consistently high sub-surface temperatures fail to provide the cool microclimate refuge that pikas require during daytime hours in summer. Of the 17 patches

in which surveyors documented minimum sub-surface temperatures $> 58^{\circ}\text{F}$, eight had no pikas and only three had more than three pikas. Further, two of the three patches having more than three pikas were at elevations $> 1,600$ m.

Multiple habitat and temporal factors affected temperature changes between the talus surface and sub-surface. As hypothesized, the temperature change was negatively correlated with surface temperature, elevation, depth beneath the surface, and northerly aspects, and positively correlated with a quadratic time of day covariate in the top models. These results suggest that the temperature change becomes more negative (i.e., the temperature drop increases) as surface temperatures rise, which is expected because sub-surface temperatures increase at a slower rate during the day than surface temperatures. The quadratic time effect suggests that the temperature change is smaller at early morning and evening hours, and greatest during the middle of the day when surface temperatures are likely to be highest. Therefore, pikas would be most susceptible to thermal stress at the surface during late morning through afternoon hours, but these times also provide the greatest benefit to remain under the talus. This effect would be more pronounced at lower elevations because model results suggest that the temperature change is less at lower compared to higher elevations. Smith (1974b) documented pika surface activity by hour and found that during summer months pikas remained largely inactive at the surface from late morning through afternoon at lower elevations, but activity increased in early morning and evening hours. At high elevations, pikas were active on the surface during all hours of the day (Smith 1974b). Higher elevations not only experience lower day time temperatures than lower elevations, but they also have lower night temperatures that may dramatically cool areas beneath the talus surface, thereby allowing sub-surface microclimates to remain cool even as surface temperatures rise throughout the day. In patches with greater depths beneath the talus surface, the space and increased rock structure may exist to trap cold air even during the warmest summer days. Indeed, model results suggest that as depth increases the temperature drop increases, thereby making patches with greater sub-surface depths potentially more favorable to pika thermoregulation. The probability of pika patch use was positively correlated with depth, although its confidence intervals slightly spanned zero in the top model.

4C. Effects of Resource Availability on Pika Abundance

Talus patch perimeter was significant in the top approximating models, suggesting abundance was affected by resource availability. As hypothesized, total pika abundance in large-scale survey areas was positively correlated with the total perimeter of talus patches in the area. On small scales, pika abundance in talus patches was positively correlated with the perimeter of individual patches. Also, the probability of patch use was positively correlated with patch perimeter, although confidence intervals slightly overlapped zero. Patches with larger perimeters offer resources to support greater numbers of pikas as they allow more pikas to forage at the patch edge, and provide increased thermal cover and protection from predators beneath talus. Combined with the need for resources is the territorial behavior of pikas (Peacock 1997). Because pikas establish territories as individuals (Smith and Weston 1990), patches with larger perimeters are more likely to support a higher number of territories. Further, exploratory analyses indicated that patch perimeter was a better predictor of abundance than area, which corroborates findings from Franken and Hik (2004). Because pikas require talus for thermal cover and predator protection, they must either forage near the patch edge or access vegetation within the patch boundary to minimize thermal stress and predation risk. The total perimeter of talus in survey areas was positively correlated with the elevation of the area, indicating an increased availability of talus habitat at higher elevations. However, the amount of variability in the data that was explained by elevation alone was relatively low (i.e., $R^2 = 0.35$), and the extent of correlation between perimeter and elevation was minimal enough such that multicollinearity was not a problem in the modeling analysis. Therefore, including both perimeter and elevation together in the same model provided insights to how each covariate may influence abundance.

4D. Influence of Trails on the Probability of Talus Patch Use

The probability of pika patch use was positively correlated with the distance to the nearest trail. This suggests that the probability of pikas occupying a patch was greater in patches farther from trails. Human presence on trails may result in pikas not colonizing certain patches owing to disturbance. Increased vigilance by pikas when monitoring trails for people may result in decreased time foraging and stocking haypiles, which may ultimately negatively impact survival and recruitment. However, the result should be considered with some hesitancy because the majority of patches surveyed were not close enough to trails for pika behavior to be affected

by human presence (Appendix A, Figures A1 and A2). Of the 20 patches located within 100 m of a trail, seven were not occupied by pikas. Further, abundance in these 20 patches ranged from 0 to 21 pikas with a mean of 5.2 pikas (SE = 1.6), but 14 patches had three or fewer pikas. While distance to campsites was not significant in any top models examining patch use or abundance, most talus patches that were surveyed and close to campsites were occupied by pikas in relatively high abundance. Notable examples include camps at Copper Lake, Fisher Creek, Sourdough Mountain, and Thornton Lakes. Because pikas are vigilant for unexpected predators, ephemeral human presence on trails may have a greater influence on patch occupancy than do camps at which people are present for extended periods of time, which may allow for pika habituation. The disturbance of marmots (*Marmota* spp.), which at times coexist with pikas in talus patches and also alert each other of predator presence through alarm calls, by hikers has been shown to be greater in areas less frequently visited by people (Neuhaus and Mainini 1998). This suggests marmots habituate to human presence near trails that have repeated use. No literature exists on how human activity affects pika behavior, habitat use, and survival and, therefore, more data are needed to examine whether human recreation affects pika occupancy of patches or abundance.

4E. Study Limitations and Future Considerations

While the results of this study present many new and insightful findings into pika ecology in the North Cascades National Park Service Complex and elsewhere, it should be cautioned that conclusions are drawn from only one year of data and experiences. Interannual climate variability can have major impacts on seasonal and annual pika survival rates, and recruitment (Smith 1978, Kreuzer and Huntly 2003). Additionally, pika populations that are stable often exist in a dynamic equilibrium in which population numbers may oscillate greatly among years, with the extent of the fluctuations possibly dependent on habitat quality (Smith 1980, Southwick et al. 1986, Morrison and Hik 2008a). Because only one year of data was available from this study it is unknown whether some survey area populations are stable or unstable, and whether areas with low pika abundance in 2009 will remain low in future years or see significant growth as part of natural fluctuations. The influence of certain climate, habitat, and anthropogenic factors may also be more pronounced in other years and, therefore, additional data collection is needed to better determine these effects. Many covariates that were not included in the top

models did have significant statistical relationships with abundance and the probability of patch use when evaluated by themselves, and these effects could be elucidated with additional data. Habitat use/availability analyses are most useful in determining factors affecting use when the actual probability of use is small (Keating and Cherry 2004). In part, because 74% of patches surveyed were occupied by pikas, my habitat use analyses failed to document many significant covariates in the top models. Continued data collection to document variability in patch occupancy is needed, as is addition of more patches and survey areas to the sample. Finally, limitations existed in using climate covariates in the analyses because I had to use SNOTEL station data to predict snow pack, temperature, and precipitation attributes, and temperature measurements obtained during habitat data collection were collected on one specific date. While snow pack snow water equivalent was included in many top models, the date of snowmelt covariate failed to yield any insights. Because temperature and the date of snowmelt have been documented to be important factors affecting pika ecology from other studies (Smith 1974b, Kreuzer and Huntly 2003, Morrison and Hik 2007), deploying data loggers at and below the talus surface in occupied and unoccupied patches would be extremely beneficial. Temperature data collected year-round specifically in pika habitat would provide detailed information on maximum and minimum summer and winter temperatures, and their associated variability, and knowledge of the date of snowmelt within each patch.

Pika populations in the North Cascades ecosystem were affected by climate and habitat attributes acting across multiple scales. Climate and habitat factors interact to control resource availability for any species, which subsequently helps determine animal distributions over time (Fretwell and Lucas 1969, Fretwell 1972). A primary question in devising management and conservation plans is whether the portion of a population that exists in low and marginal quality habitats has high enough survival and reproductive rates to sustain population growth (Shaffer 1981, Pulliam and Danielson 1991). Because of the uncertainties associated with climate change with respect to large- and small-scale climate variability within and among years, and habitat-related changes, understanding the role of marginal habitats relative to a species' life history is essential. This is particularly true for species whose dispersal ability is limited and redistribution to higher quality habitat may not be possible. Further degradation of the quality of low and marginal habitats because of climate change related impacts might result in local-scale extirpations in the short-term, which may eventually lead to large-scale extirpations.

5. MANAGEMENT IMPLICATIONS

5A. *Considerations for Annual Monitoring*

Because pika populations were affected by multiple climate and habitat factors on large and small scales, most notably elevation and temperature, the potential exists for pikas to be adversely affected by climate change in NOCA. While short- and long-term effects of climate change are uncertain, pika abundance was correlated with temperature and snow covariates, which are two climate attributes that will be affected should global warming persist (Leung and Wigmosta 1999). Abundance was also correlated with elevation, which provides a surrogate measure of climate conditions and resource availability. Despite these potential threats to the species, pikas were abundant at mid to high elevations and were widely distributed in talus patches across most elevations in the park. The overall population estimate for pikas in NOCA was 22,279 pikas with a 95% confidence interval of 6,706 to 37,852 pikas. Because the defined sampling universe consisted of survey areas within 3 km of a trail or road, which encompassed approximately 65% of the park, the estimate only pertains to this region. The remaining 35% of NOCA also includes substantial amounts of potential pika habitat at mid to high elevations and, therefore, the number of pikas within the entire park is likely to be greater than the estimate. Despite the relatively large overall population estimate, it is worth noting the small estimates at lower elevations. For elevations < 914 m, there were an estimated 426 pikas with a 95% confidence interval of 0 to 1,139 pikas. Also, at elevations between 914 and 1,218 m, there were an estimated 719 pikas with a 95% confidence interval of 0 to 2,101 pikas. The risk of extirpation is highest for these lower elevation populations because they are already faced with higher summer temperatures and foraging on vegetation that is likely of lower quality than that at higher elevations. Continued temperature increases and precipitation changes from climate warming may result in conditions that are not suitable for pika survival at low elevations in NOCA. In contrast, the patches at higher elevations that were also found to be at low pika densities may provide more suitable habitat should climate warming persist. Earlier dates of snowmelt associated with climate warming would provide a longer growing season for vegetation that currently does not exist and that might currently preclude pikas from existing at higher densities. Therefore, in the short term, higher elevation areas may provide “compensatory” habitat suitable for pikas that may offset population losses at lower elevations.

Overall, additional data collection on abundance, habitat, and climate variability is needed from pika populations at all elevations.

Results from this study can be used as a baseline for future pika monitoring within NOCA. Additionally, the U.S. Forest Service can apply the sampling design used for this work to devise new pika monitoring efforts on National Forest lands within the North Cascades ecosystem. Because the size of pika populations may fluctuate widely among years (Franken 2002, Morrison and Hik 2008a), at the onset of monitoring I recommend annual surveys of each patch within each survey area. Specifically for NOCA, annual resurveys of the patches and survey areas that were surveyed in 2009 would provide the most benefit. Repeating surveys every other year, or even less frequently, would fail to document natural variability in pika populations and provide insufficient data to make conclusions about long-term population trends. Annual surveys are also needed to determine variability in abundance among years for each survey area, which would then facilitate power analyses to determine how long each area population needs to be monitored to determine a significant trend. Morrison and Hik (2008a) employed an approach that used seven or more years of abundance data from several populations that varied by patch aspect to examine how long each population would need to be monitored to determine a trend. While the habitat data collection used for this study provided valuable insights on factors affecting various aspects of pika ecology, monitoring could be continued only with surveys for the purpose of providing abundance estimates. The large-scale abundance analysis from this work used covariates that can be derived from GIS layers, SNOTEL station climate data, and data gathered in 2009 on patch size and vegetation cover. The data required for the analysis could be updated annually, the models refit and evaluated, and the results would be available in a timely fashion for management purposes. However, if funding is available to complete habitat data collection with the surveys, then it is preferable to continue to amass data on vegetation cover and temperature profiles for the purposes of examining long-term changes of both in pika habitat and updating models from the small-scale analyses. As noted above, deployment of temperature data loggers would also provide extremely valuable insights into year-round temperature variability specifically in pika habitat that would preclude use of SNOTEL data for estimating the date of snowmelt and large-scale trends in temperature.

5B. Population Variability Considerations

Based on the sample size of 30 survey areas and variability documented in mean pika abundance in survey areas in 2009, a 50% decrease in mean abundance is detectable at a power of 0.8. To document an increase or decrease in mean pika abundance at a power of 0.8, a 57% change is detectable. Until several years of data on pika abundance in NOCA is gathered to determine the extent of variability between and among years, it is difficult to determine whether a 50% decline is a cause for concern in terms of species conservation. Major declines have occurred in other pika populations across large scales in one or two years that are attributed to difficult winter conditions for pika survival (Morrison and Hik 2007, Morrison and Hik 2008a). Morrison and Hik (2008a) documented a 90% decline over two years in the populations they were monitoring, which they suggested was caused by low snow accumulation during the coldest months, more frequent freezing and thawing events, winter rains, and increased snow accumulation during spring that delayed the emergence of vegetation. Certainly, increasing the sample size of survey areas to more than 30 would be beneficial to be able to detect smaller declines in mean abundance and accumulating more information on distribution and habitat use throughout NOCA. However, sample sizes of 40 and 70 areas would be required to detect declines $< 43\%$ and $< 32\%$, respectively, the latter of which would require more than doubling the field effort and resources employed in 2009. The possibility also exists of surveying different survey areas and patches on an annual basis, which would afford accumulation of habitat use data and snapshots of abundance and patch occupancy across a greater portion of NOCA.

Because climate related influences on population abundance are likely to be specific to elevation, it may be worth evaluating changes in mean abundance for each of the five elevation strata. Based on the number of areas surveyed in 2009, the 1,219 to 1,523 m and 1,524 to 1,827 m strata had large enough sample sizes and low enough CVs to detect a meaningful decline in mean population size. At a power of 0.8, mean stratum population declines of 72% and 73% can be detected for the 1,219 to 1,523 m and 1,524 to 1,827 strata, respectively. The combination of sample sizes and high CVs for the ≤ 913 m, 914 to 1,218 m, and $\geq 1,828$ m strata precluded obtaining a power of 0.8 for even a 100% decline in the mean stratum population size. To detect at least an 80% decline in mean stratum population size, the sample size must be increased to > 12 areas for the ≤ 913 m stratum, > 19 areas for the 914 to 1,218 m stratum, and > 9 areas for the

$\geq 1,828$ m stratum. A 50% decline in mean population size is detectable for the 1,219 to 1,523 m stratum with a sample size of > 12 areas, and for the 1,524 to 1,827 m stratum with > 17 areas.

5C. Future Detectability Studies

The repeat surveys in the eight survey areas provided insights into variability in the number of pikas counted in each area. The number of pikas enumerated in patches is most likely to vary because of juvenile emergence and dispersal, and detectability, which may be affected by weather conditions and the date of the survey. The top model from the analysis examining factors influencing variability in pikas counted per survey contained a significant, positive date of survey covariate. The positive correlation between the number of pikas counted and survey date suggests that more pikas were counted in surveys conducted later in the summer than earlier within the same survey areas. This result is supported by field observations of increased numbers of haypiles from mid-August through September that increased detectability of pikas. Further, the proportion of pika locations from haypiles also increased as the summer progressed. The standard error of the average number of pikas counted for each survey area was positively correlated with the number of pikas counted, suggesting that more variability existed in the population estimate for larger populations. Therefore, given the variability in counts and increased detectability later in summer, one survey of each survey area and patch per year would provide information on the minimum number of pikas. Surveys scheduled for late summer and early fall would provide the most accurate assessment of pika abundance.

To obtain more precise survey area population estimates from data gathered over an entire summer, completion of a detectability study is highly recommended. To address this recommendation, there are three options.

1. Conduct surveys only from mid-August through early October. This is a time at which all juveniles would have emerged from the talus and likely dispersed, haypiles would be most detectable and therefore abundance counts would be most accurate, and daytime temperature may be cooler and afford more visual locations at the talus surface. A drawback of this approach would be availability of student field technicians that could only work through August. If one was trying to survey a large number of survey areas or patches as done in 2009, then the only way to accomplish this in less than two months would be to hire a crew of five to six people and divide them into two groups to survey the survey areas. One

possibility to consider if employing this approach is poor weather for surveys, which is something countered several times in 2009.

2. Annually continue the repeat surveys that were started in 2009 and use them to construct a model of estimated abundance as done with the 2009 data. Conducting repeated surveys each year would allow one to develop a model of “corrected” abundance and correct counts from each year to afford comparisons of counts among years. The advantage of this method is that surveys could be conducted anywhere that is snow free from June until early October. The disadvantage is the effort required conducting repeated surveys and accessing these patches multiple times within a summer.
3. As part of mark-recapture surveys one could conduct multiple observational surveys, similar to that done in 2009, at regular intervals in a patch to determine how count varies with weather conditions and the time of year. These surveys would also provide a measure of how many marked pikas, and the proportion of the population, that are actually observable at the talus surface during surveys. The drawbacks of this method are that one needs to be conducting a mark-recapture survey in a survey area or devoting a crew to spending considerable time in one area throughout the summer, which would preclude surveys in other areas.

5D. Future Work to Examine Vital Rates

Beyond continuing the population monitoring and habitat and climate data collection initiated with this study, it would be beneficial for NOCA to begin a study on pika vital rates to determine how survival rates and recruitment are affected by climate, habitat, and anthropogenic factors. Because pika vital rates may vary with habitat quality (e.g., Kreuzer and Huntly 2003) and quality may vary with elevation based on the pika densities documented from this study, I recommend using study populations from at least three different elevation ranges. One population should be selected from low (< 1,219 m), middle (1,219 to 1,827 m), and high (> 1,827 m) elevations. If funding exists to add additional study populations, then it may be possible to also choose populations based on their location relative to the two divides. Because of the difficulty of off-trail access to many patches and the need for carrying traps and additional equipment to conduct mark-recapture surveys, accessibility is one factor that should be

considered when choosing populations to study. However, care also needs to be made to ensure that the populations are not selected simply for convenience, which may bias findings.

Estimator precision increases with increasing capture (resight) probability and increased sampling (Williams et al. 2002), and therefore, intensive capture and resight efforts are important. Comparisons provided by Pollock et al. (1990) document for a sample of 40% of individuals at relatively small population sizes (i.e., 50 individuals), the coefficient of variation for a survival estimate ranges between 0.1-0.4 as capture probability decreases from 1.0 to 0.8. Likewise, for the same sample and population size, the coefficient of variation for a population estimate ranges between 0.05-0.30 as capture probability decreases from 1.0 to 0.8 (Pollock et al. 1990). To determine a significant difference in survival rates among three survey populations at a power of 0.8 and significance level of 0.05, the smallest detectable effect size increases with decreasing sample size of pikas (Table 6). At a 100% recapture probability, 14 and 322 pikas must be marked to detect effect sizes of 0.5 and 0.1, respectively (Table 6). At an 80% recapture probability, 17 and 403 pikas must be marked to detect effect sizes of 0.5 and 0.1, respectively (Table 6). Surveyors counted 17 or more pikas in 14 survey areas and 40 or more pikas in seven areas in 2009. Of the 14 survey areas with 17 or more pikas, two were < 1,219 m, 11 were between 1,219 and 1,827 m, and one was > 1,827 m in elevation. Because connectivity for pika dispersal among patches may exist across survey area boundaries, I recommend expanding the boundaries of any survey area used in mark-recapture work to incorporate all patches that could be used by the population.

Finally, deployment of temperature data loggers is needed to obtain fine-scale temperature data as part of the mark-recapture work. Because of the need for climate data specific to pika habitat at and below the talus surface in talus patches, collaborative opportunities with other climate researchers are likely to be limited. Hoary marmots (*Marmota caligata*) sometimes coexist with pikas in talus patches throughout NOCA (J. Bruggeman *unpublished data*, R. Christopherson *unpublished data*) and it may be possible to deploy loggers to simultaneously obtain climate data relevant to both species' ecology. Therefore, collaborations between research efforts on pikas and marmots should be explored.

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7. TABLES

Table 1. The estimated pika population size and 95% confidence intervals for all survey areas contained within each of the five elevation strata in the North Cascades National Park Service Complex.

Elevation Stratum	Population Estimate (95% confidence interval)
< 914 m	426 (0, 1,139)
914 to 1,218 m	719 (0, 2,101)
1,219 to 1,523 m	4,698 (1,043, 8,353)
1,524 to 1,827 m	9,671 (3,393, 15,409)
≥ 1,828 m	6,765 (0, 21,323)

Table 2. Coefficient estimates and 95% confidence intervals (CI) for covariates contained in each of the three top approximating models with $\Delta AIC_c < 2$ from the modeling analysis examining factors influencing pika abundance on the talus patch scale ($ABUNDANCE_{patch}$). Covariates with estimates that are significant at $\alpha = 0.05$ are denoted with bold. An “N/A” denotes the covariate was not included in the model. Covariates are defined in the text.

Covariate	Model #1	Model #2	Model #3
	$\Delta AIC_c = 0.00$	$\Delta AIC_c = 1.02$	$\Delta AIC_c = 1.73$
	Estimate (95% CI)	Estimate (95% CI)	Estimate (95% CI)
<i>Intercept</i>	2.77 (2.19, 3.35)	3.21 (2.65, 3.76)	2.91 (2.25, 3.58)
<i>PERIMETER_{patch}</i>	2.21 (1.63, 2.79)	2.56 (1.99, 3.13)	2.22 (1.64, 2.81)
<i>DISTPATCH_{patch}</i>	N/A	N/A	0.21 (-0.23, 0.66)
<i>TEMPMAX</i>	0.87 (0.31, 1.44)	N/A	0.86 (0.29, 1.43)
<i>TEMPMAX_{time}</i>	0.16 (-0.56, 0.89)	N/A	0.17 (-0.56, 0.89)
<i>TEMPMIN</i>	-1.11 (-1.85, -0.37)	-0.92 (-1.64, -0.19)	-1.17 (-1.91, -0.42)
<i>TEMPMIN_{time}</i>	0.43 (-0.44, 1.31)	0.69 (0.07, 1.31)	0.46 (-0.42, 1.34)
<i>TEMPDATE</i>	0.84 (0.30, 1.38)	0.46 (-0.05, 0.96)	0.81 (0.26, 1.36)
<i>TEMPMAX * TEMPMAX_{time}</i>	-0.10 (-1.10, 0.90)	N/A	-0.09 (-1.08, 0.91)
<i>TEMPMAX * TEMPDATE</i>	-0.82 (-1.65, 0.01)	N/A	-0.77 (-1.62, 0.08)
<i>TEMPMIN * TEMPMIN_{time}</i>	0.61 (-0.81, 2.03)	0.76 (-0.55, 2.06)	0.66 (-0.78, 2.09)
<i>TEMPMIN * TEMPDATE</i>	0.65 (-0.42, 1.72)	0.17 (-0.84, 1.19)	0.50 (-0.62, 1.63)

Table 3. The eight top approximating models with $\Delta AIC_c < 2$ for the *a priori* modeling analysis examining factors influencing the probability of talus patch use by pikas. Listed for each model are the ΔAIC_c value, the number of parameters (K), and the Akaike weight (w). Covariates are defined in the text.

Model Structure	ΔAIC_c	K	w
$\beta_0 + \beta_1 * PERIMETER_{patch} + \beta_2 * DISTTRAIL_{patch} + \beta_3 * TEMPMIN + \beta_4 * TEMPMIN_{time} + \beta_5 * TEMPDATE + \beta_6 * DEPTH_{patch} + \beta_7 * TEMPMIN * TEMPMIN_{time} + \beta_8 * TEMPMIN * TEMPDATE$	0.00	9	0.102
$\beta_0 + \beta_1 * PERIMETER_{patch} + \beta_2 * DISTTRAIL_{patch} + \beta_3 * TEMPMIN + \beta_4 * TEMPMIN_{time} + \beta_5 * TEMPDATE + \beta_6 * TEMPMIN * TEMPMIN_{time} + \beta_7 * TEMPMIN * TEMPDATE$	0.43	8	0.082
$\beta_0 + \beta_1 * PERIMETER_{patch} + \beta_2 * DISTTRAIL_{patch} + \beta_3 * TEMPMIN + \beta_4 * TEMPMIN_{time} + \beta_5 * TEMPMAX + \beta_6 * TEMPMAX_{time} + \beta_7 * TEMPDATE + \beta_8 * TEMPMIN * TEMPMIN_{time} + \beta_9 * TEMPMIN * TEMPDATE + \beta_{10} * TEMPMAX * TEMPMAX_{time} + \beta_{11} * TEMPMAX * TEMPDATE$	0.85	12	0.066
$\beta_0 + \beta_1 * PERIMETER_{patch} + \beta_2 * DISTTRAIL_{patch} + \beta_3 * ASPECT_{patch} + \beta_4 * TEMPMIN + \beta_5 * TEMPMIN_{time} + \beta_6 * TEMPMAX + \beta_7 * TEMPMAX_{time} + \beta_8 * TEMPDATE + \beta_9 * TEMPMIN * TEMPMIN_{time} + \beta_{10} * TEMPMIN * TEMPDATE + \beta_{11} * TEMPMAX * TEMPMAX_{time} + \beta_{12} * TEMPMAX * TEMPDATE$	1.17	19	0.056
$\beta_0 + \beta_1 * PERIMETER_{patch} + \beta_2 * DISTTRAIL_{patch} + \beta_3 * TEMPMIN + \beta_4 * TEMPMIN_{time} + \beta_5 * TEMPDATE + \beta_6 * DEPTH_{patch} + \beta_7 * COVER_{patch} + \beta_8 * TEMPMIN * TEMPMIN_{time} + \beta_9 * TEMPMIN * TEMPDATE$	1.26	10	0.054
$\beta_0 + \beta_1 * PERIMETER_{patch} + \beta_2 * DISTTRAIL_{patch} + \beta_3 * TEMPMIN + \beta_4 * TEMPMIN_{time} + \beta_5 * TEMPDATE + \beta_6 * DISTTRAIL_{patch} + \beta_7 * TEMPMIN * TEMPMIN_{time} + \beta_8 * TEMPMIN * TEMPDATE$	1.27	9	0.054
$\beta_0 + \beta_1 * PERIMETER_{patch} + \beta_2 * DISTTRAIL_{patch} + \beta_3 * TEMPMIN + \beta_4 * TEMPMIN_{time} + \beta_5 * TEMPDATE + \beta_6 * COVER_{patch} + \beta_7 * TEMPMIN * TEMPMIN_{time} + \beta_8 * TEMPMIN * TEMPDATE$	1.59	9	0.046
$\beta_0 + \beta_1 * PERIMETER_{patch} + \beta_2 * TEMPMIN + \beta_3 * TEMPMIN_{time} + \beta_4 * TEMPDATE + \beta_5 * DEPTH_{patch} + \beta_6 * TEMPMIN * TEMPMIN_{time} + \beta_7 * TEMPMIN * TEMPDATE$	1.62	8	0.045

Table 4. Model averaged coefficient estimates and 95% confidence intervals (CI) for covariates contained in the eight top approximating models with $\Delta AIC_c < 2$ from the *a priori* modeling analysis examining factors influencing the probability of talus patch use by pikas. Covariates with estimates that are significant at $\alpha = 0.05$ are denoted with bold. Covariates are defined in the text.

Covariate	Model Averaged Coefficient Estimate (95% CI)
<i>Intercept</i> (<i>ASPECT</i> _{patch} = <i>east</i>)	9.45 (1.20, 17.70)
<i>PERIMETER</i> _{patch}	6.83 (-1.73, 15.39)
<i>DISTTRAIL</i> _{patch}	3.11 (-0.23, 6.44)
<i>DISTPATCH</i> _{patch}	1.08 (-0.79, 2.94)
<i>DEPTH</i> _{patch}	1.57 (-0.38, 3.52)
<i>COVER</i> _{patch}	0.74 (-0.62, 2.10)
<i>ASPECT</i> _{patch} = <i>north</i>	1.51 (-1.90, 4.93)
<i>ASPECT</i> _{patch} = <i>northeast</i>	3.84 (0.35, 7.34)
<i>ASPECT</i> _{patch} = <i>northwest</i>	0.21 (-4.64, 5.05)
<i>ASPECT</i> _{patch} = <i>south</i>	8.65 (-10.30, 27.60)
<i>ASPECT</i> _{patch} = <i>southeast</i>	-0.88 (-4.24, 2.48)
<i>ASPECT</i> _{patch} = <i>southwest</i>	-0.44 (-3.49, 2.60)
<i>ASPECT</i> _{patch} = <i>west</i>	3.70 (-1.05, 8.44)
<i>TEMPMAX</i>	3.27 (0.91, 5.62)
<i>TEMPMAX</i> _{time}	-0.58 (-7.03, 5.88)
<i>TEMPMIN</i>	-1.79 (-4.97, 1.39)
<i>TEMPMIN</i> _{time}	1.05 (-2.00, 4.10)
<i>TEMPDATE</i>	2.70 (1.03, 4.37)
<i>TEMPMAX</i> * <i>TEMPMAX</i> _{time}	0.30 (-3.66, 4.27)
<i>TEMPMAX</i> * <i>TEMPDATE</i>	-3.77 (-7.92, 0.38)
<i>TEMPMIN</i> * <i>TEMPMIN</i> _{time}	1.54 (-3.69, 6.78)
<i>TEMPMIN</i> * <i>TEMPDATE</i>	3.54 (-0.47, 7.55)

Table 5. Coefficient estimates and 95% confidence intervals for covariates contained in each of the two top approximating models with $\Delta AIC_c < 2$ from the exploratory modeling analyses examining factors influencing the probability of talus patch use by pikas. Covariates with estimates that are significant at $\alpha = 0.05$ are denoted with bold. An “N/A” denotes the covariate was not included in the model. Covariates are defined in the text.

Covariate	Exploratory Model #1	Exploratory Model #2
	$\Delta AIC_c = 0.00$	$\Delta AIC_c =$
	Estimate (95% CI)	Estimate (95% CI)
<i>Intercept</i>	9.37 (0.57, 18.17)	8.46 (0.44, 16.48)
<i>PERIMETER</i> _{patch}	7.62 (-1.38, 16.62)	6.35 (-1.86, 14.56)
<i>DISTTRAIL</i> _{patch}	3.52 (0.08, 6.95)	3.56 (0.04, 7.08)
<i>COVER</i> _{patch}	1.57 (-0.22, 3.36)	N/A
<i>FORAGECOVER</i> _{patch}	-2.24 (-3.86, -0.62)	-1.16 (-2.67, 0.36)
<i>SWEMAX</i> _{patch}	N/A	1.82 (-0.25, 3.88)
<i>TEMPMIN</i>	-2.22 (-5.32, 0.88)	-2.22 (-5.38, 0.94)
<i>TEMPMIN</i> _{time}	0.69 (-1.40, 2.78)	0.92 (-1.23, 3.08)
<i>TEMPDATE</i>	2.16 (0.26, 4.07)	0.83 (-1.67, 3.33)
<i>TEMPMIN</i> * <i>TEMPMIN</i> _{time}	1.61 (-3.19, 6.41)	1.83 (-3.11, 6.78)
<i>TEMPMIN</i> * <i>TEMPDATE</i>	2.09 (-2.02, 6.21)	2.44 (-1.64, 6.52)

Table 6. The number of pikas that must be marked at 100% and 80% recapture probabilities to detect a given effect size at a power of 0.8 and significance level of 0.05.

Effect Size	Sample Size (Number of Marked Pikas)	
	100% Recapture Probability	80% Recapture Probability
0.1	322	403
0.2	81	102
0.3	37	46
0.4	21	26
0.5	14	17
0.6	10	12
0.7	8	10

8. FIGURES

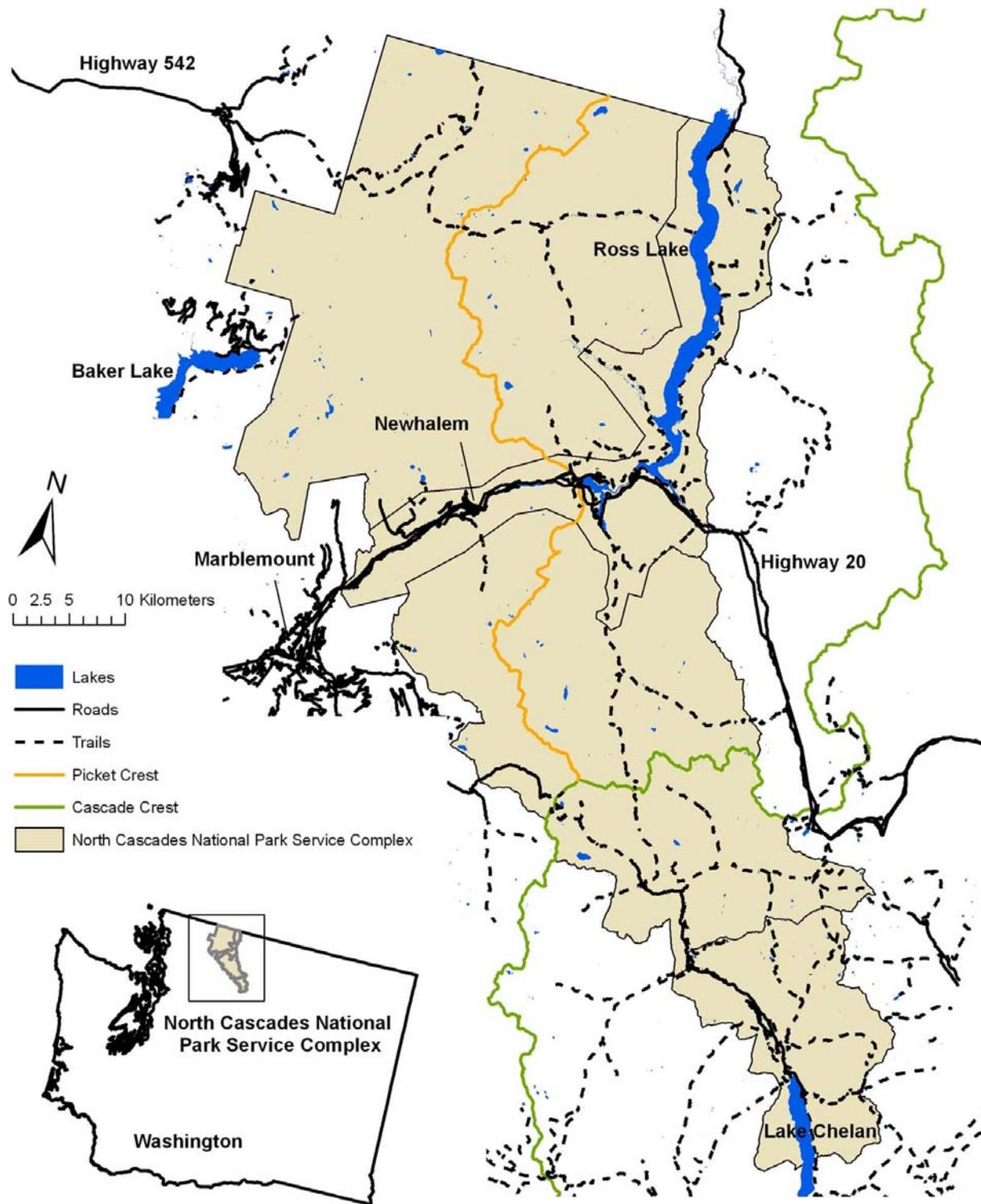


Figure 1. The study area in the North Cascades National Park Service Complex located in north central Washington.

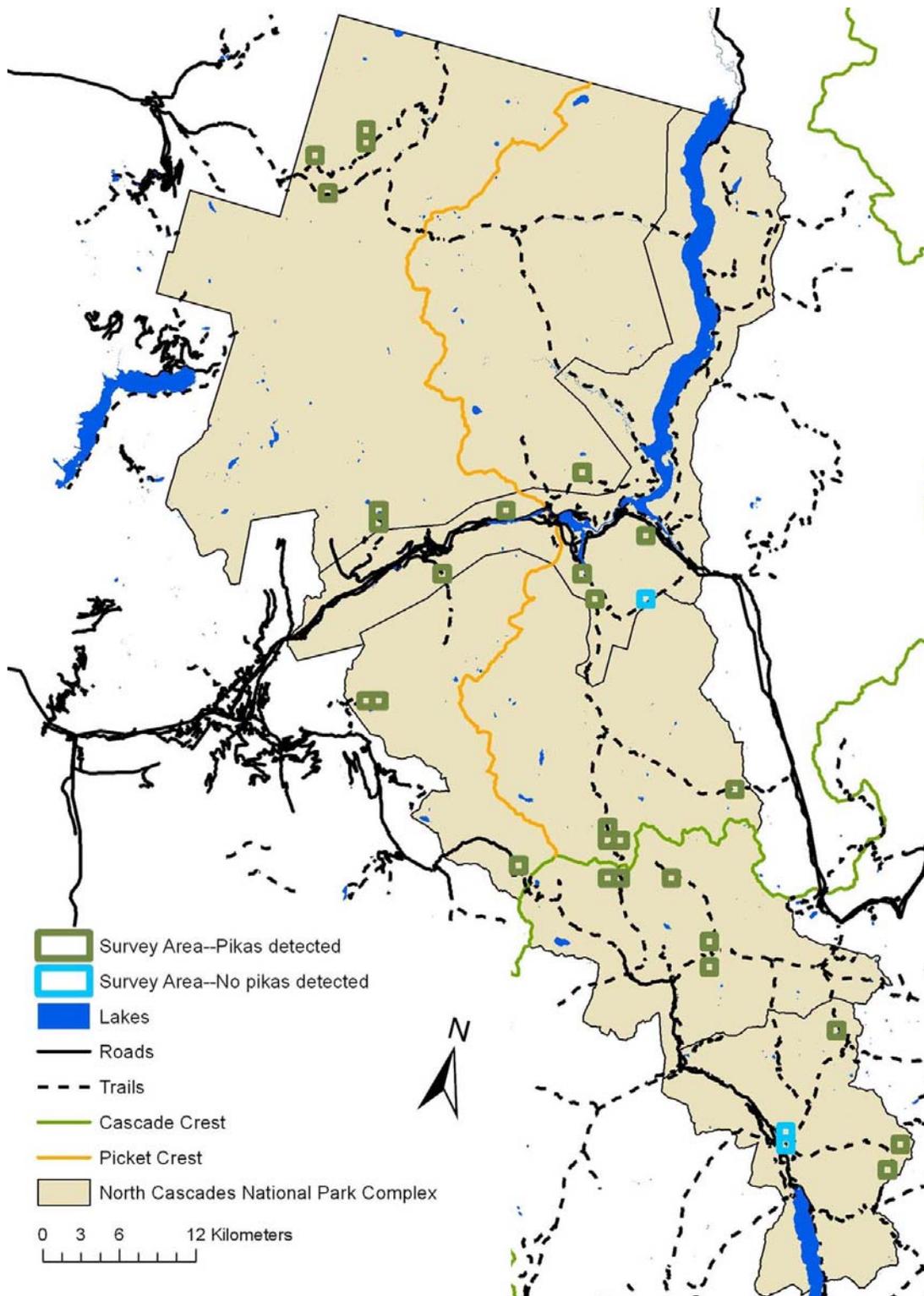
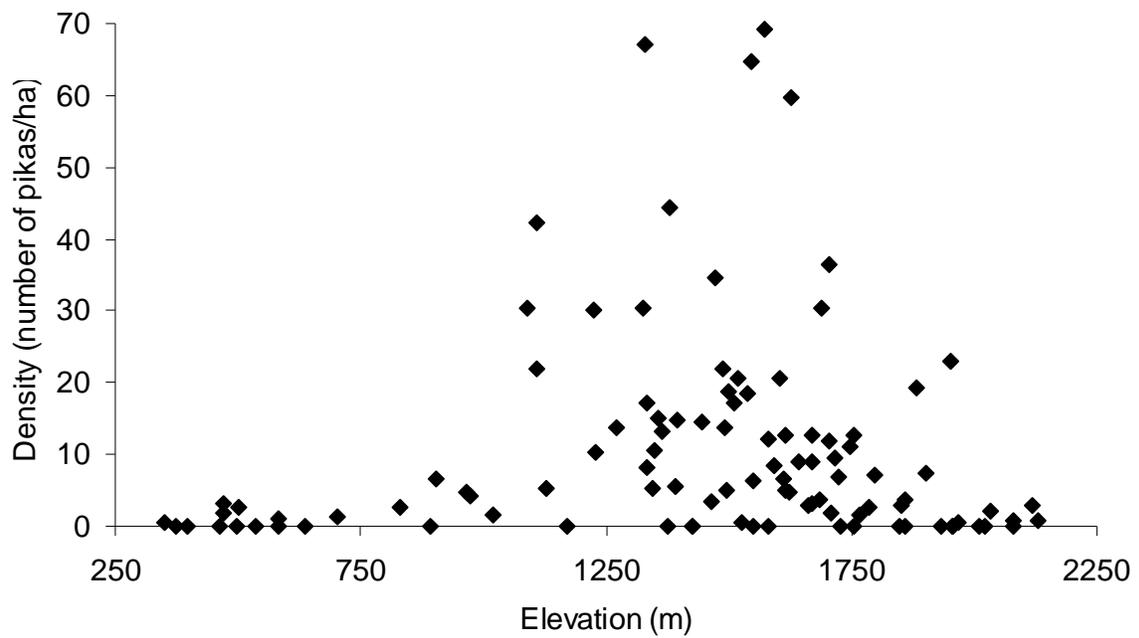
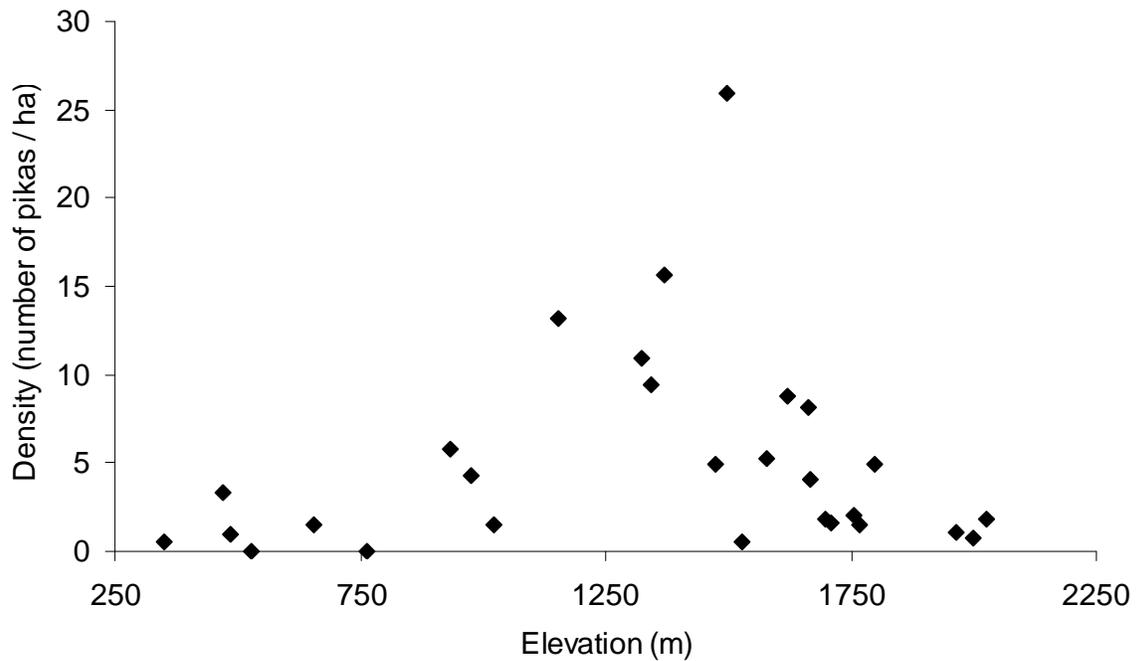


Figure 2. The 30 1-km² survey areas that were surveyed for pikas in summer 2009 in the North Cascades National Park Service Complex, Washington. Survey areas in which pikas were detected are denoted with a hollow green square while those in which pikas were not detected are depicted with a hollow light blue square.

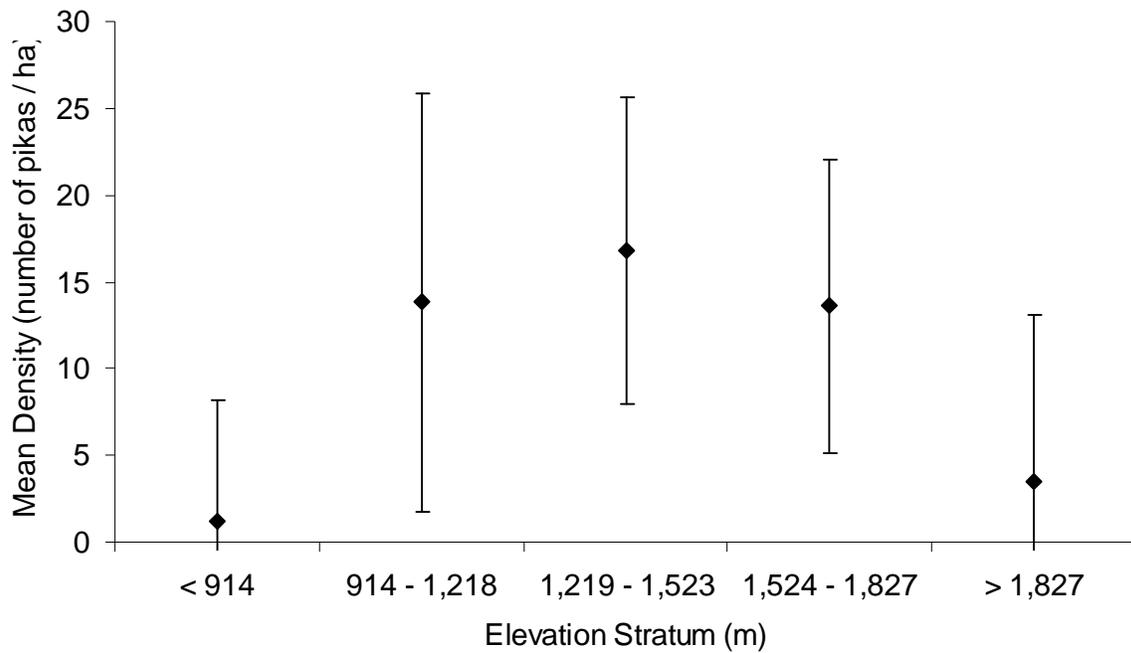


(a)

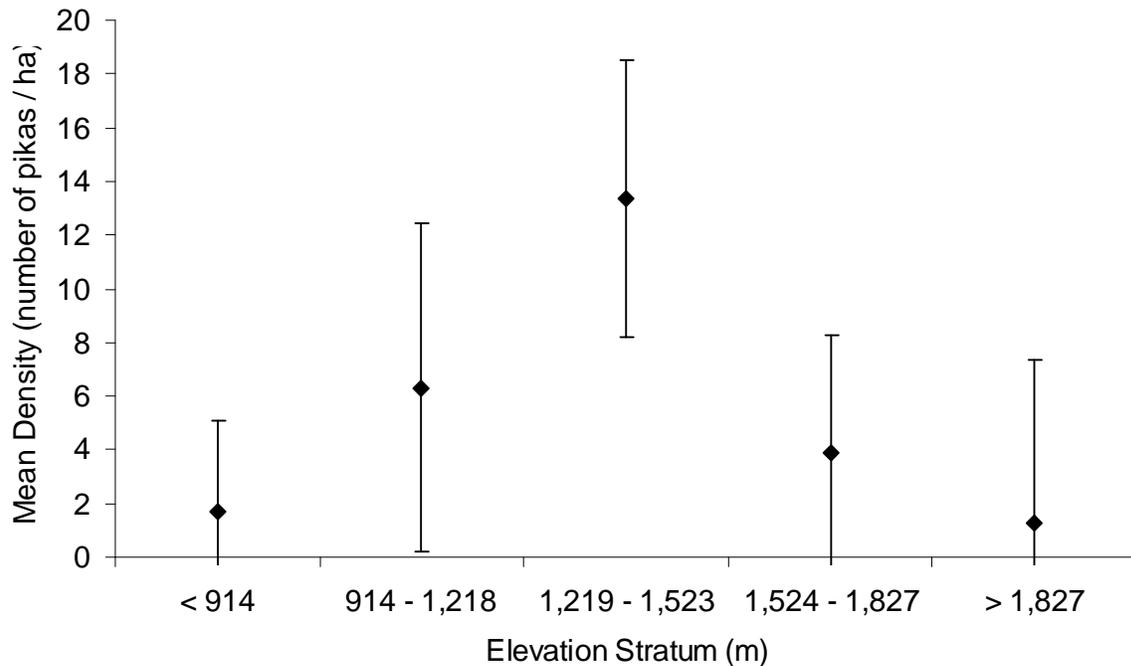


(b)

Figure 3. The variation in pika density (number of pikas per hectare) with elevation (meters) in (a) individual talus patches ($n = 102$) and (b) all talus patches combined within each of the 30 1-km² survey areas.

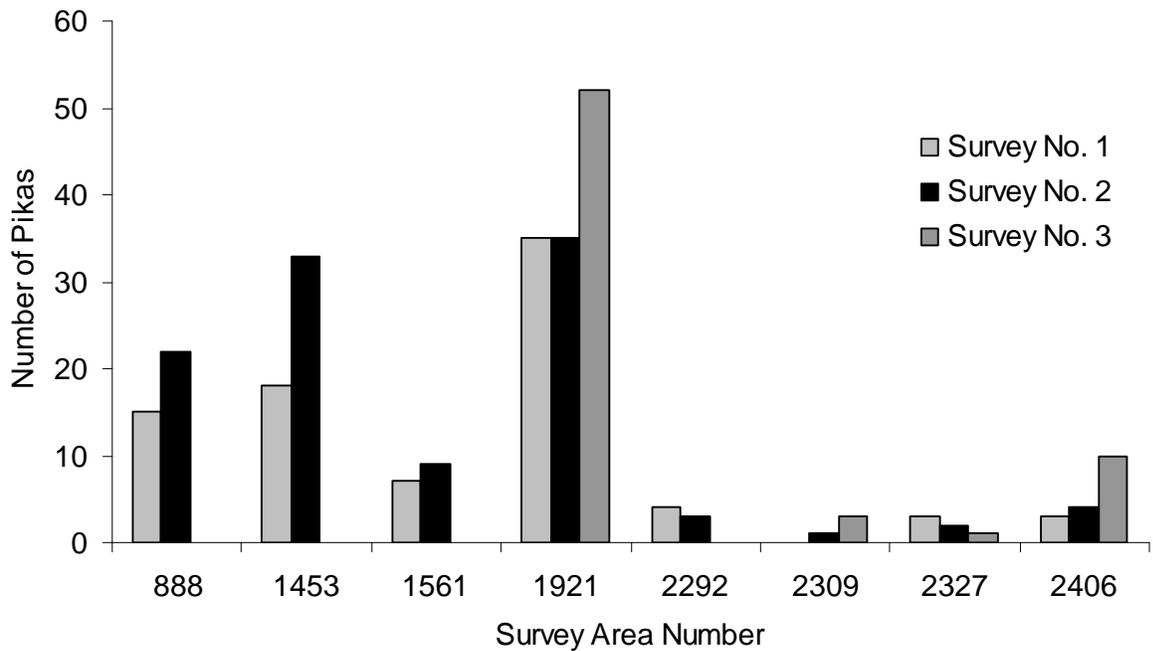


(a)

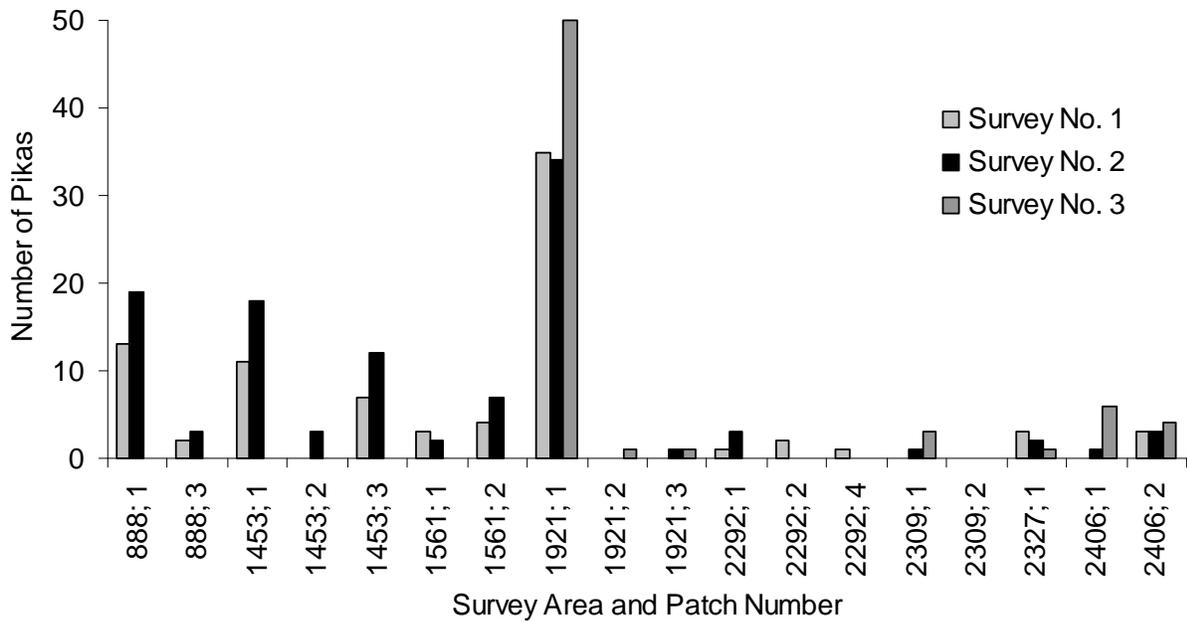


(b)

Figure 4. The mean pika density (number of pikas per hectare) and corresponding 95% confidence intervals for each of the five elevation strata (in meters) for (a) individual talus patches and (b) all talus patches combined within each of the 30 1-km² survey areas. Individual patch sample sizes for each stratum are n = 16 for < 914 m, n = 8 for 914-1,218 m, n = 26 for 1,219-1,523 m, n = 34 for 1,524-1,827 m, and n = 18 for >1,827 m. Sample sizes for survey areas by stratum are n = 7 for < 914 m, n = 3 for 914-1,218 m, n = 5 for 1,219-1,523 m, n = 10 for 1,524-1,827 m, and n = 3 for >1,827 m.

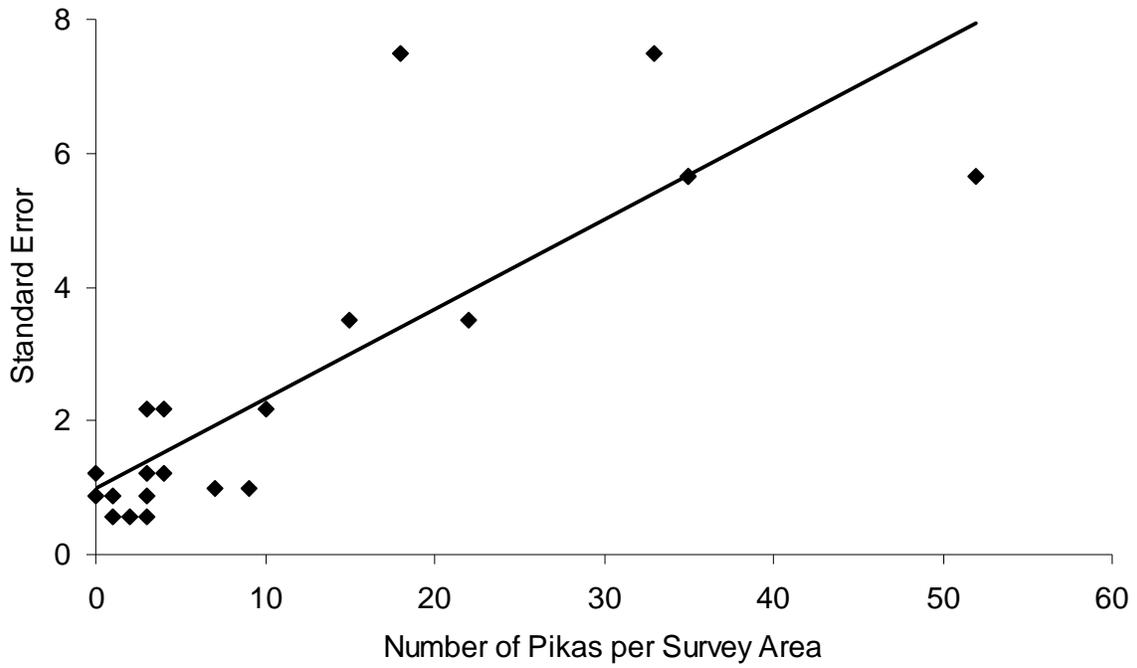


(a)

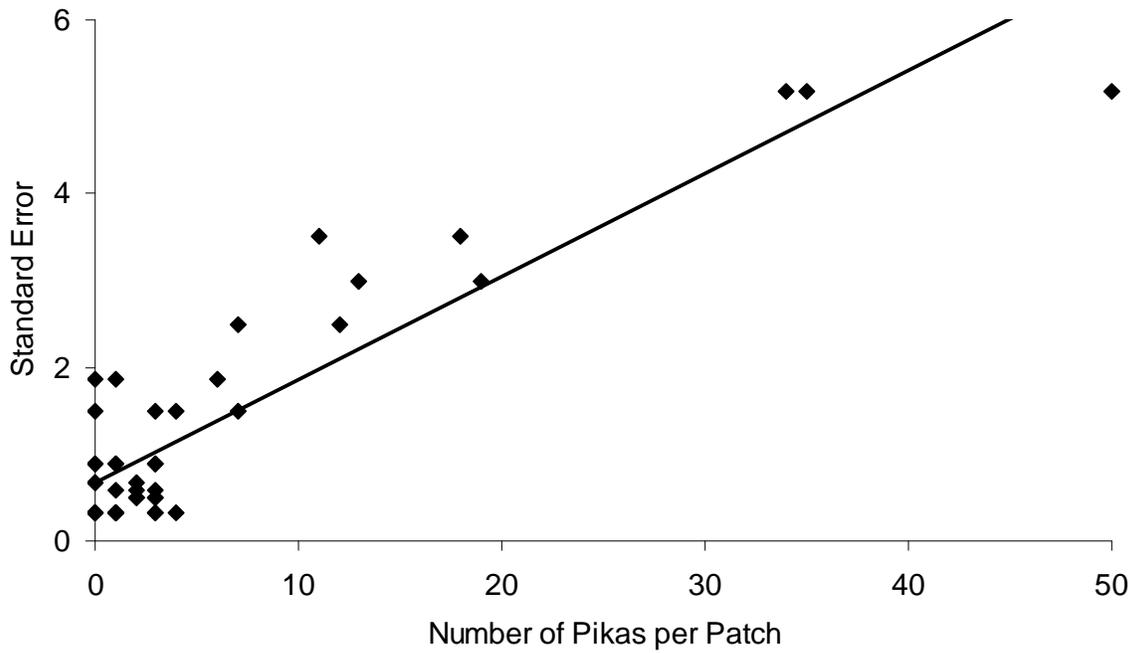


(b)

Figure 5. Variability in the number of pikas counted as part of replicate surveys conducted in (a) eight 1-km² survey areas, and (b) the 18 talus patches contained within the eight survey areas.

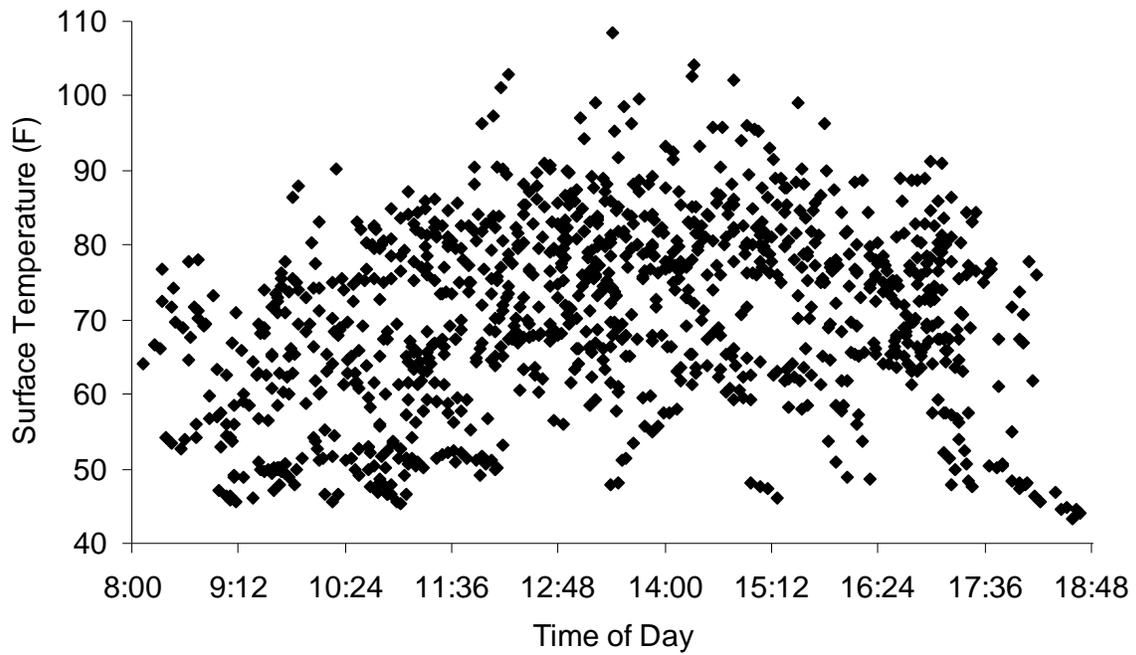


(a)

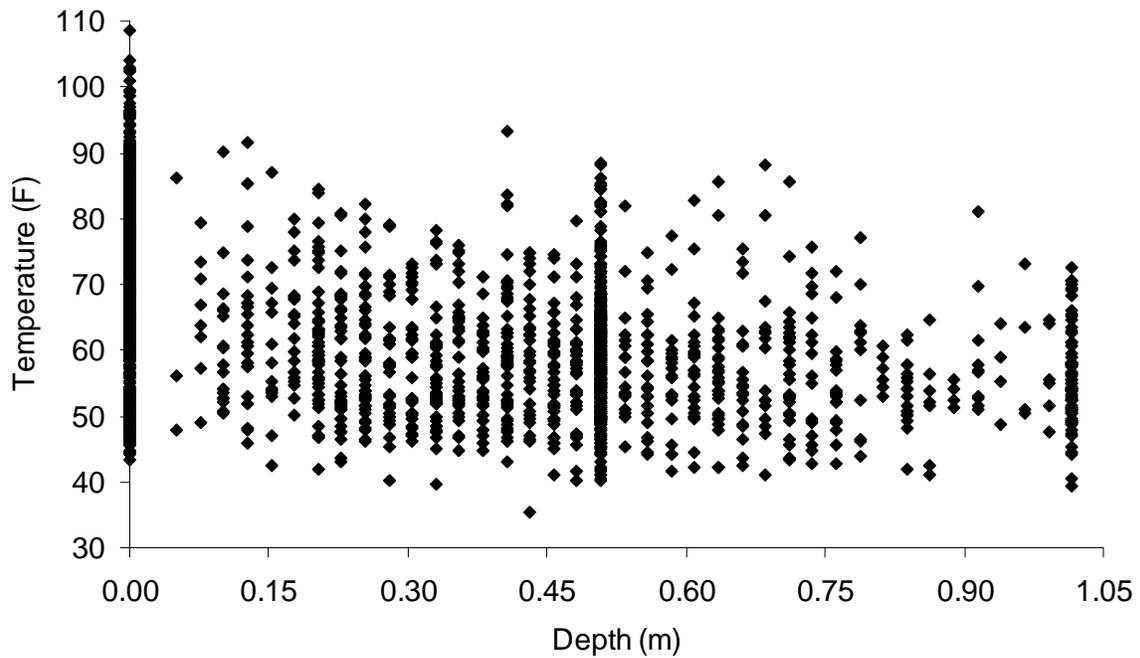


(b)

Figure 6. The standard error of the average number of pikas counted for (a) each survey area ($n = 21$) and, (b) each patch ($n = 44$) as part of repeat surveys conducted in eight survey areas and 18 patches.

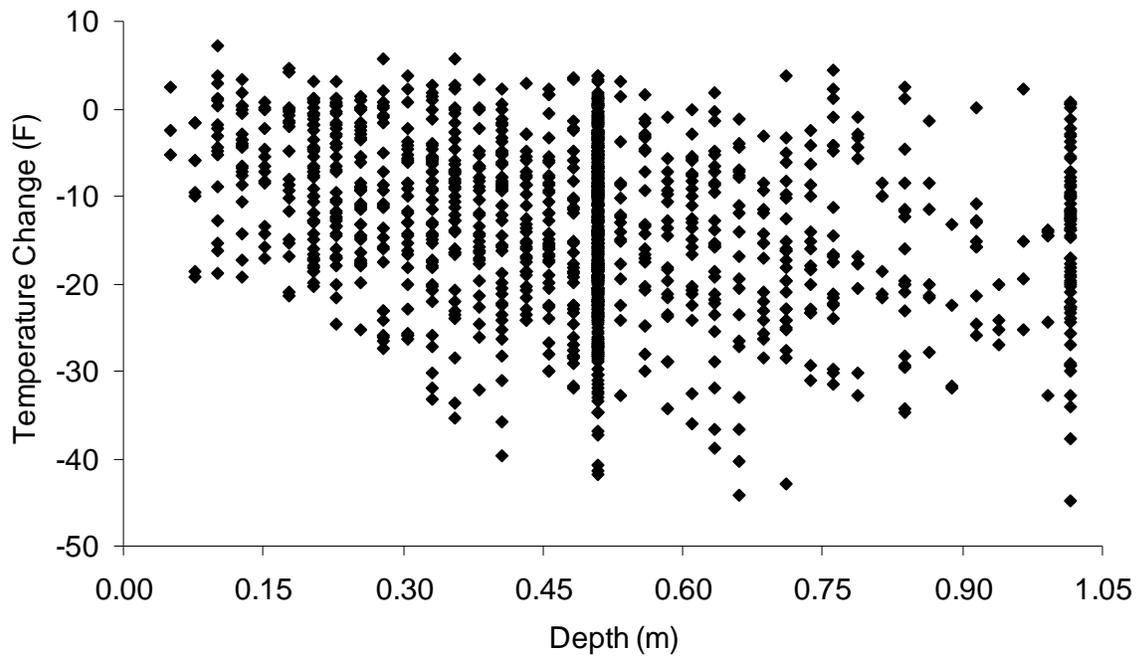


(a)

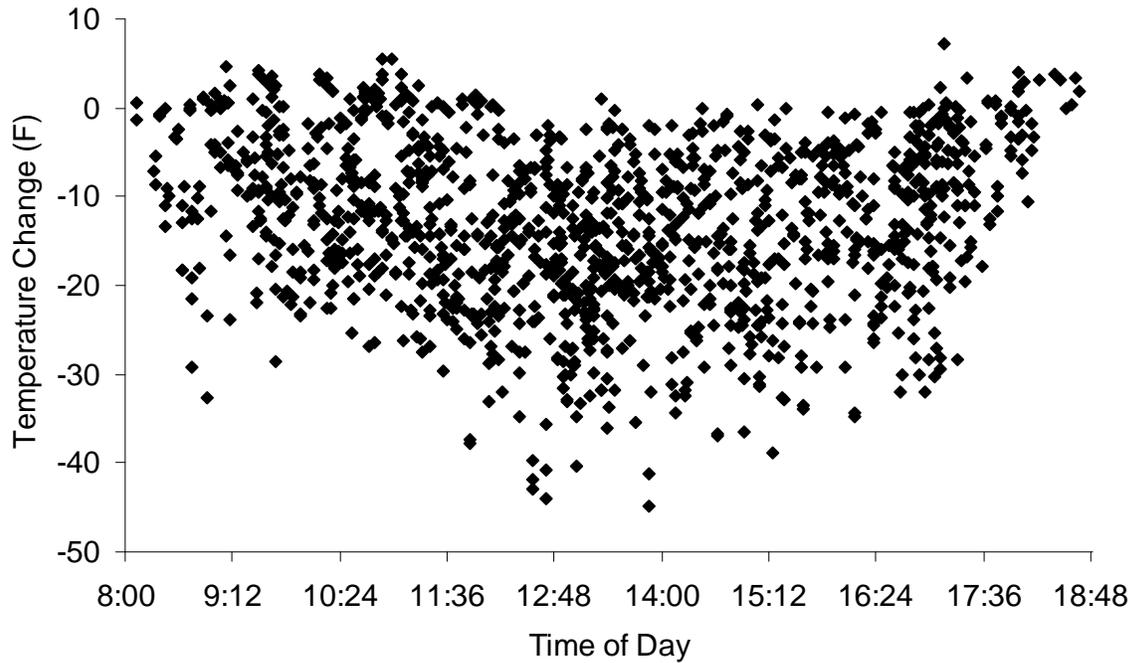


(b)

Figure 7. Temperature data collected from 1-m² plots in talus patches depicting variation in the (a) talus surface temperature (°F) with time of day (n = 1,065), and (b) temperature (°F) with depth beneath the talus surface (meters) (n = 2,260).



(a)



(b)

Figure 8. Variation in the temperature change ($^{\circ}\text{F}$) recorded between the talus surface and sub-surface ($n = 1,306$) (a) for various depths beneath the surface (meters) and (b) with the time of day. Temperature data was collected from 1-m^2 plots in talus patches.

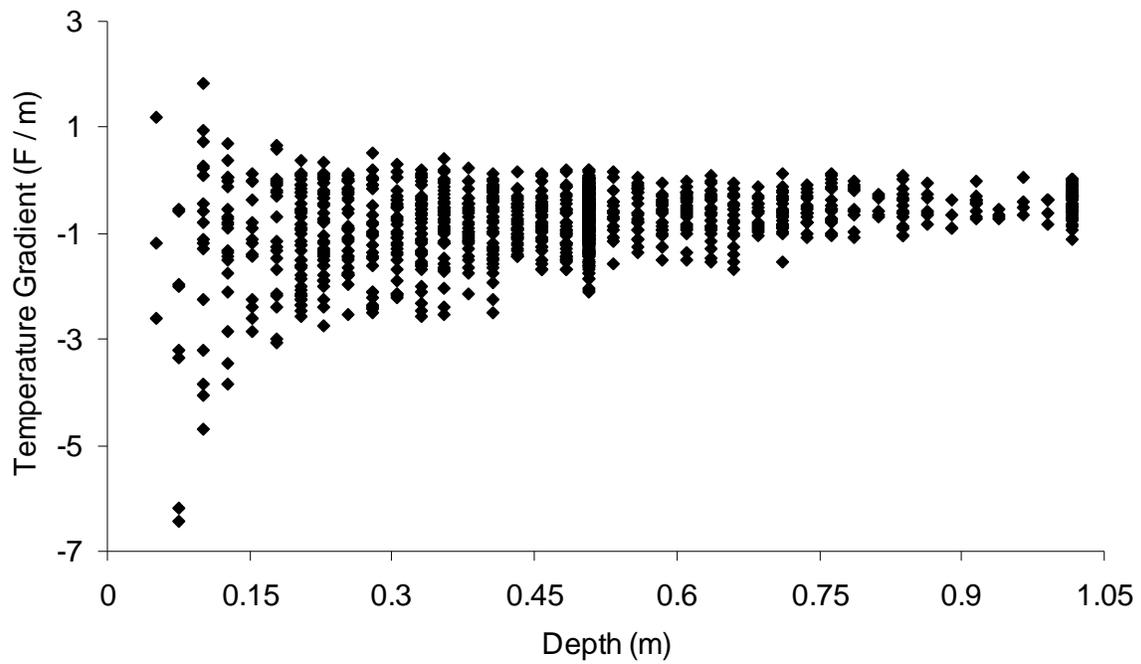
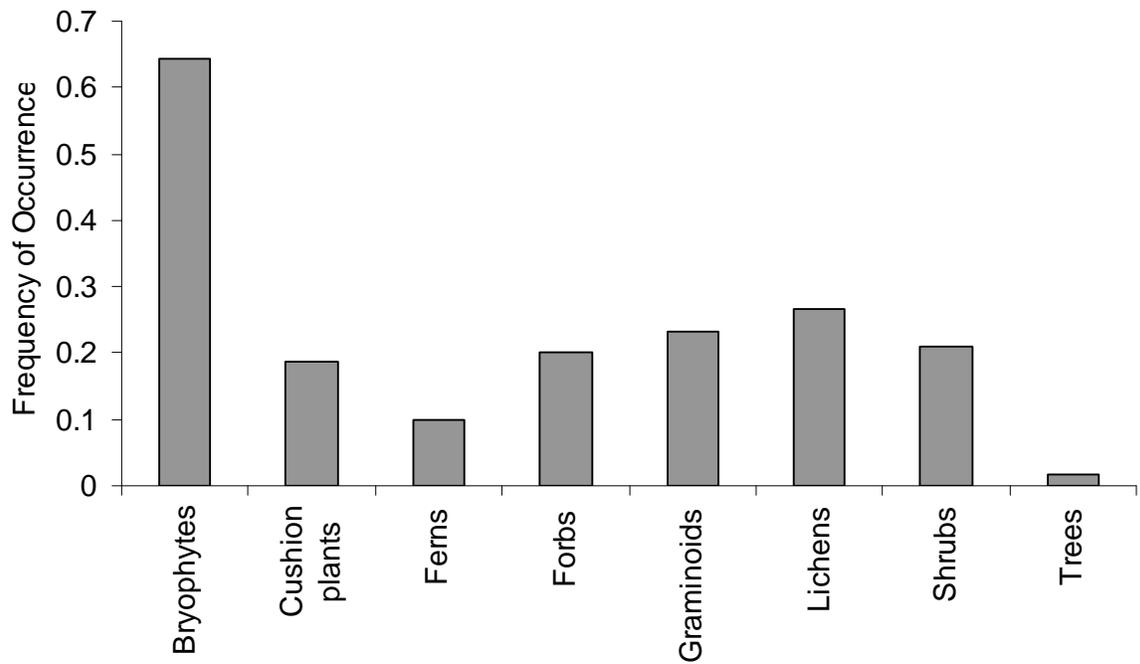
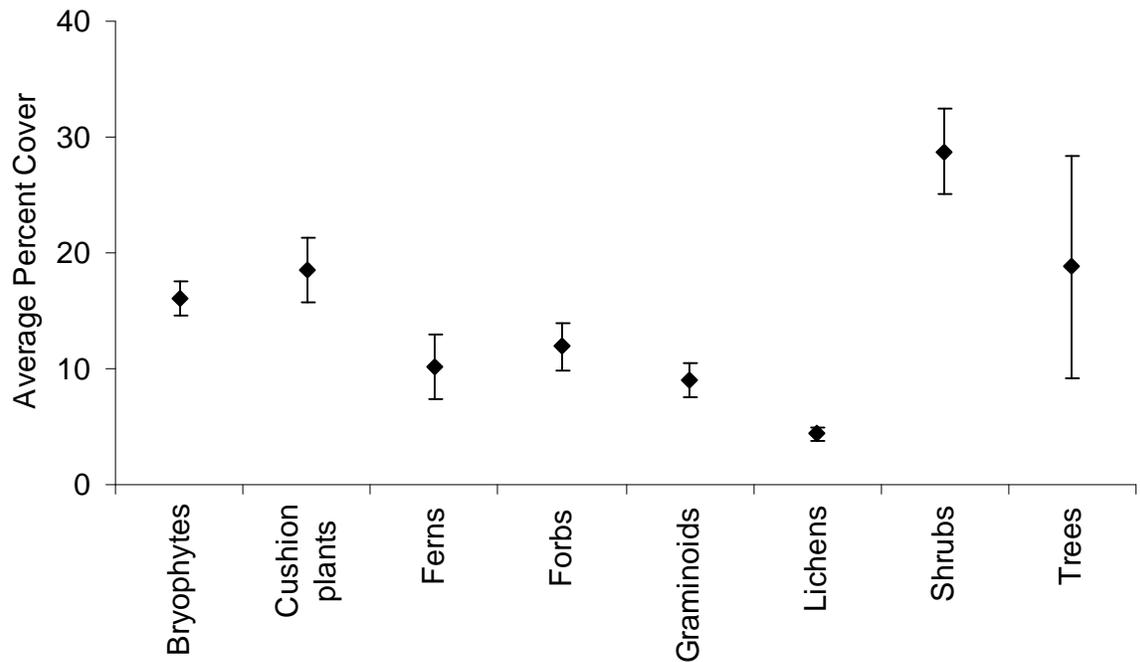


Figure 9. Variability in the temperature gradient ($^{\circ}\text{F}/\text{m}$) with depth beneath the talus surface as determined from temperature data collected from 1-m^2 plots in talus patches ($n = 1,306$). The temperature gradient was calculated as the temperature change divided by the depth at which the measurement was recorded.

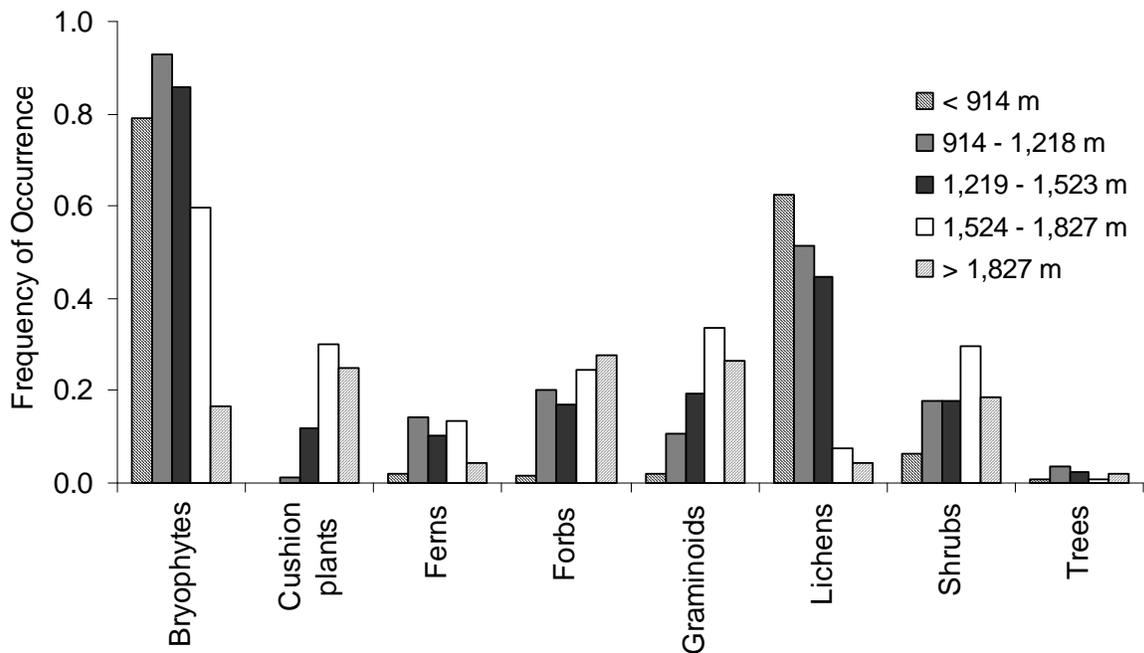


(a)

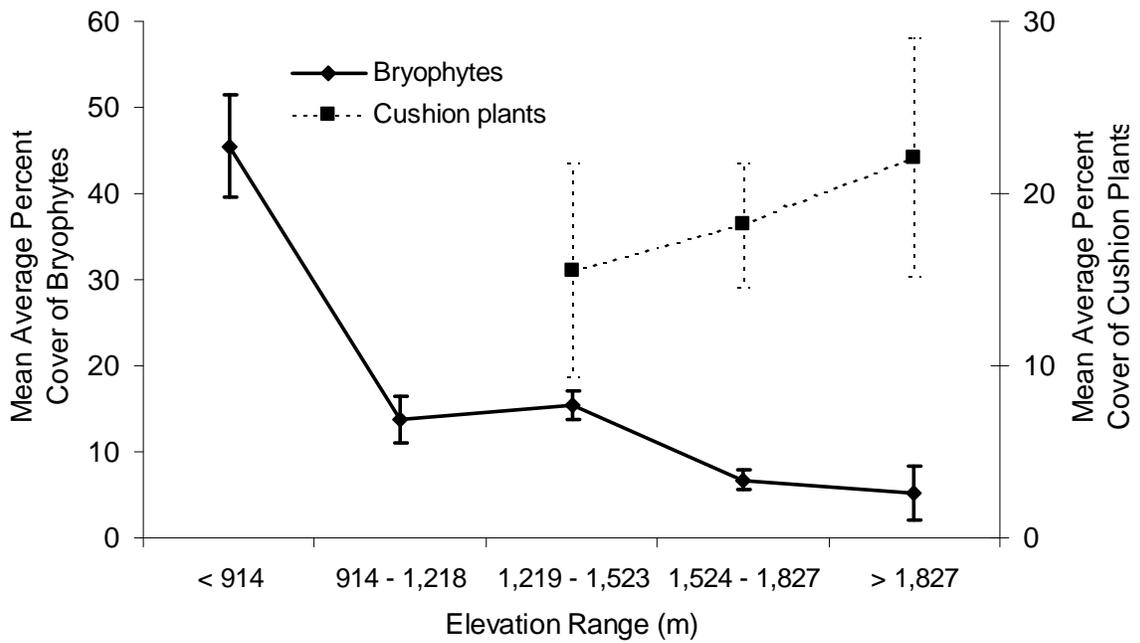


(b)

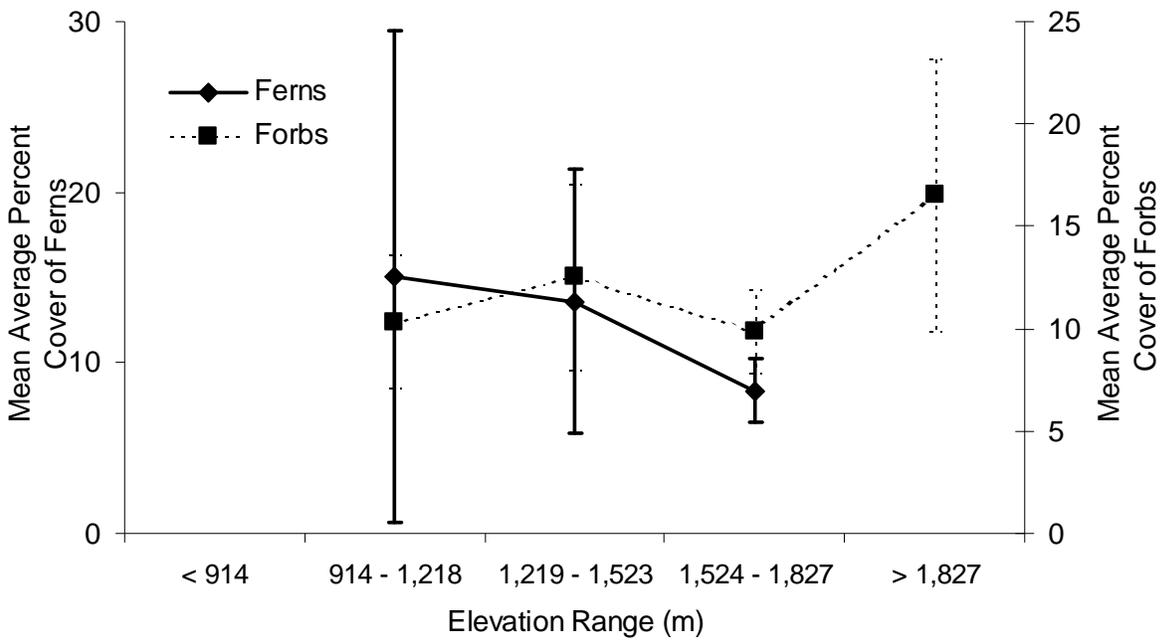
Figure 10. The (a) frequency of occurrence of vegetation cover types in talus patches, and (b) mean average percent cover of each vegetation cover type with corresponding 95% confidence intervals. Vegetation cover type data was recorded within 1-m² plots in talus patches. Samples sizes for each cover type are: bryophytes (n = 757), cushion plants (n = 221), ferns (n = 116), forbs (n = 235), graminoids (n = 273), lichens (n = 313), shrubs (n = 247), trees (n = 19)



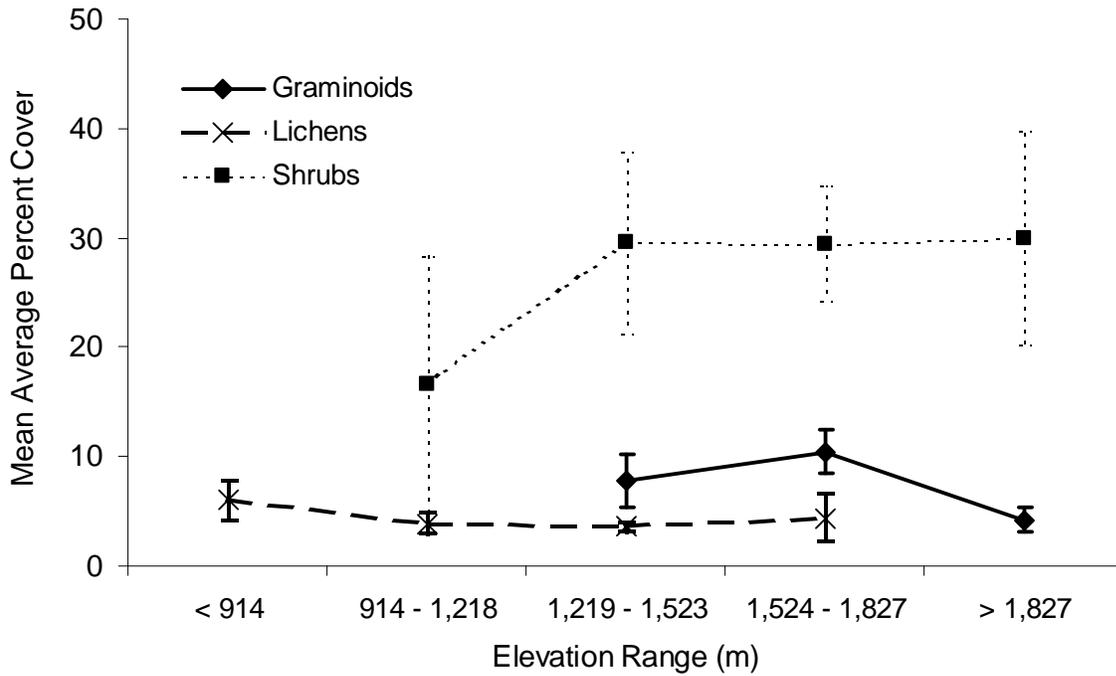
(a)



(b)

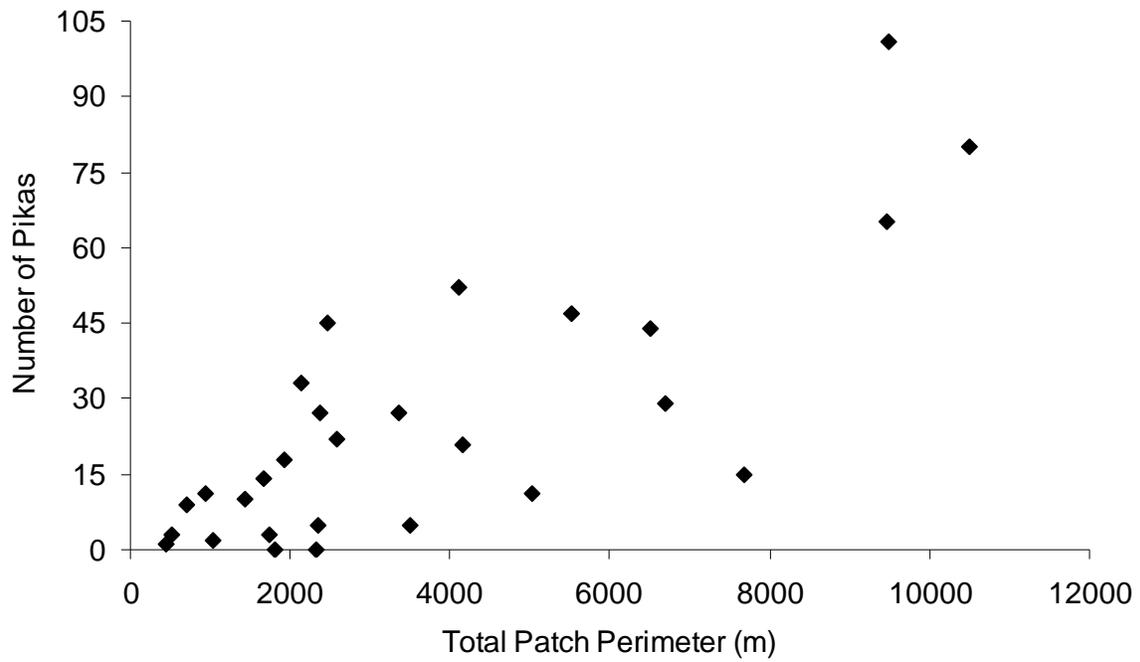


(c)

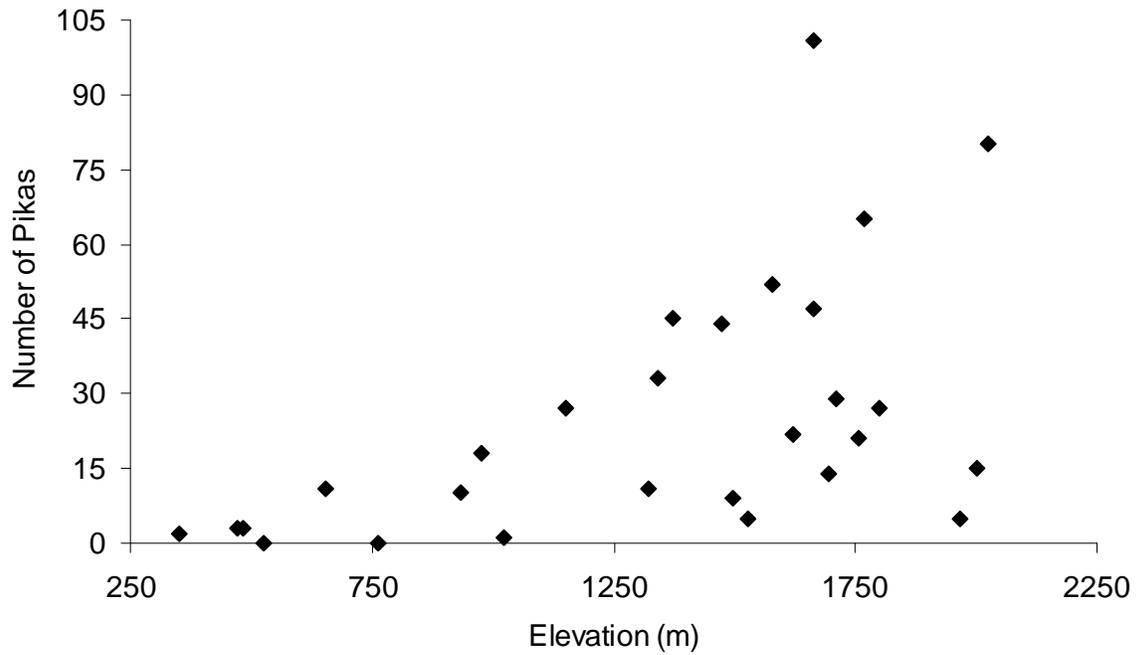


(d)

Figure 11. The (a) frequency of occurrence of vegetation cover types in talus patches by elevation stratum, and changes in mean average percent cover with elevation stratum and corresponding 95% confidence intervals of (b) bryophyte (left axis) and cushion plant (right axis) vegetation cover types, (c) fern and forb vegetation cover types, and (d) graminoid, lichen, and shrub cover types. Sample sizes for each cover type for each stratum are provided in Table A4 in Appendix A. Cover types with small sample sizes per stratum ($n < 10$) were not depicted in the figures for clarity.

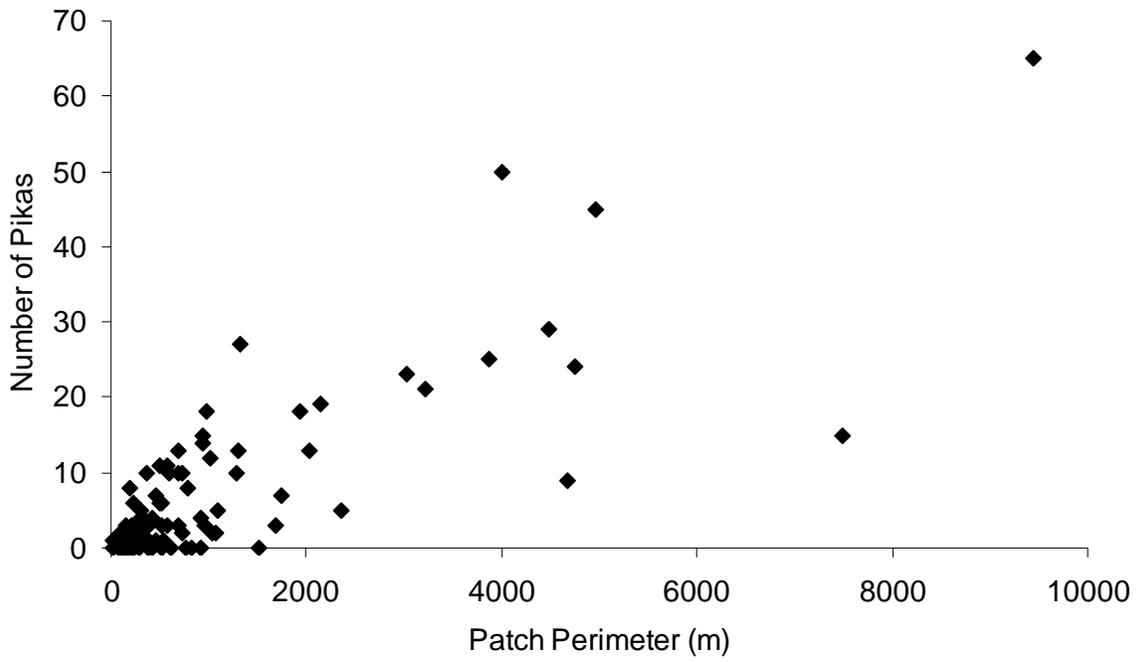


(a)

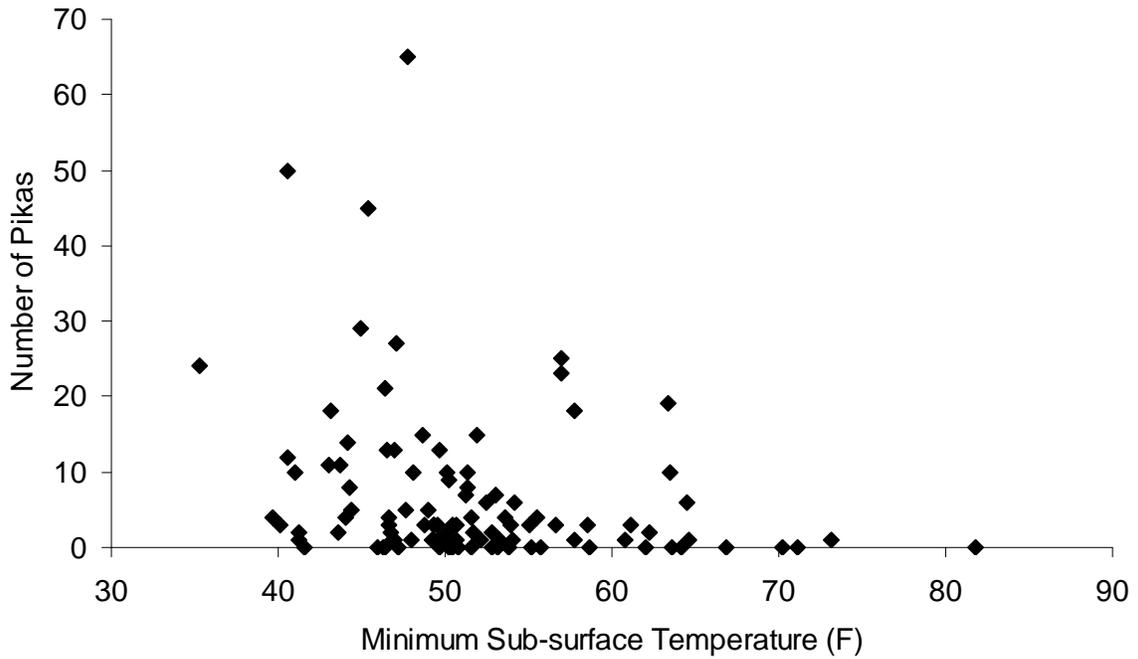


(b)

Figure 12. The relationship between the number of pikas counted in each survey area ($n = 30$) and (a) the total perimeter of all talus patches within the survey area (meters), and (b) the average survey area elevation (meters).

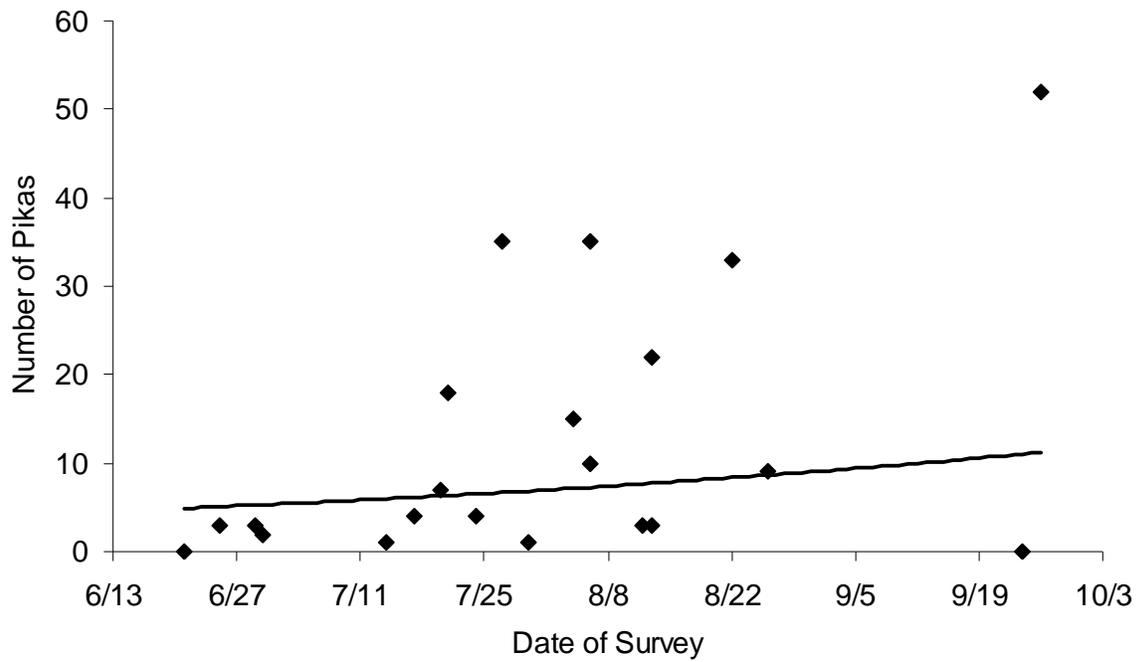


(a)

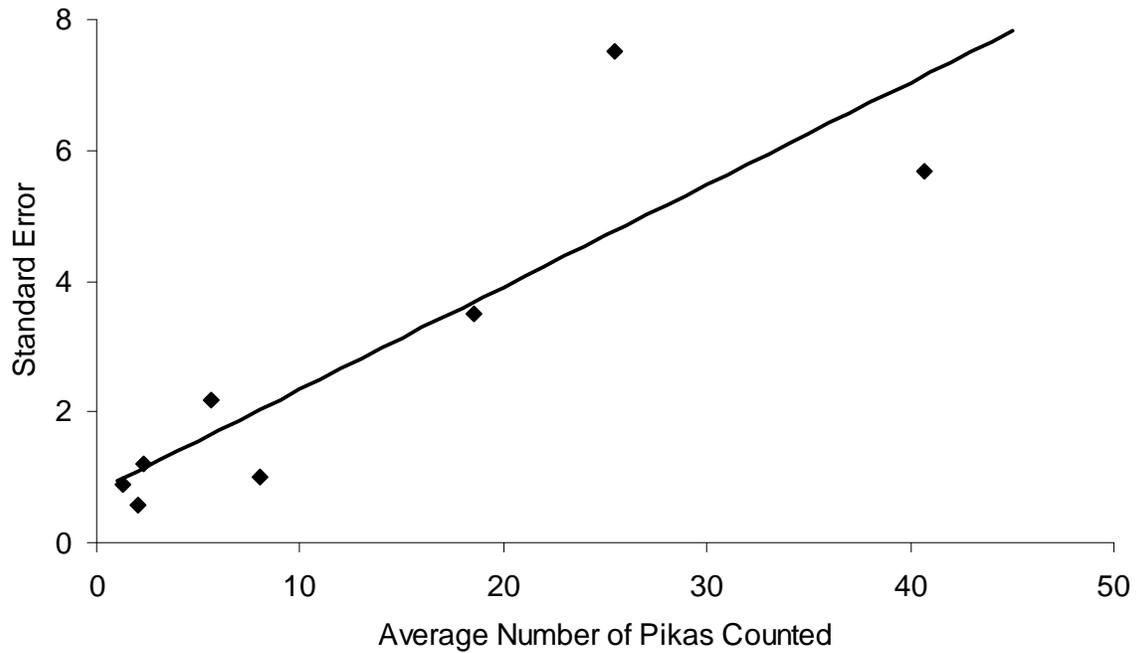


(b)

Figure 13. The relationship between the number of pikas counted in each individual talus patch ($n = 103$) and (a) talus patch perimeter (meters), and (b) the minimum temperature recorded beneath the talus surface for the corresponding patch.

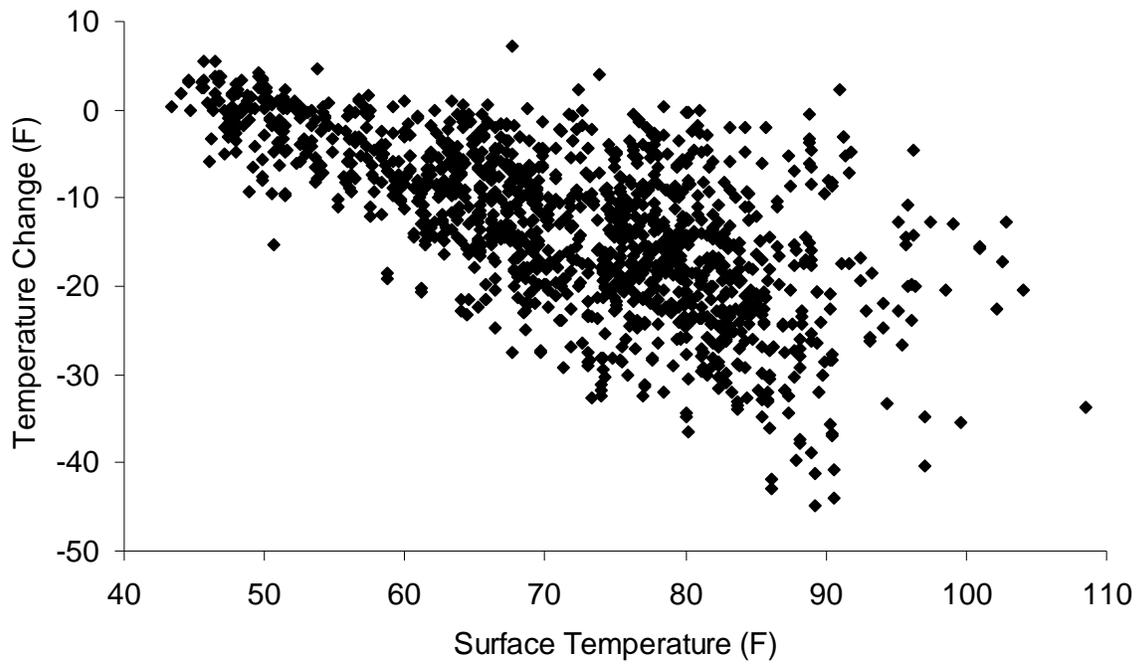


(a)

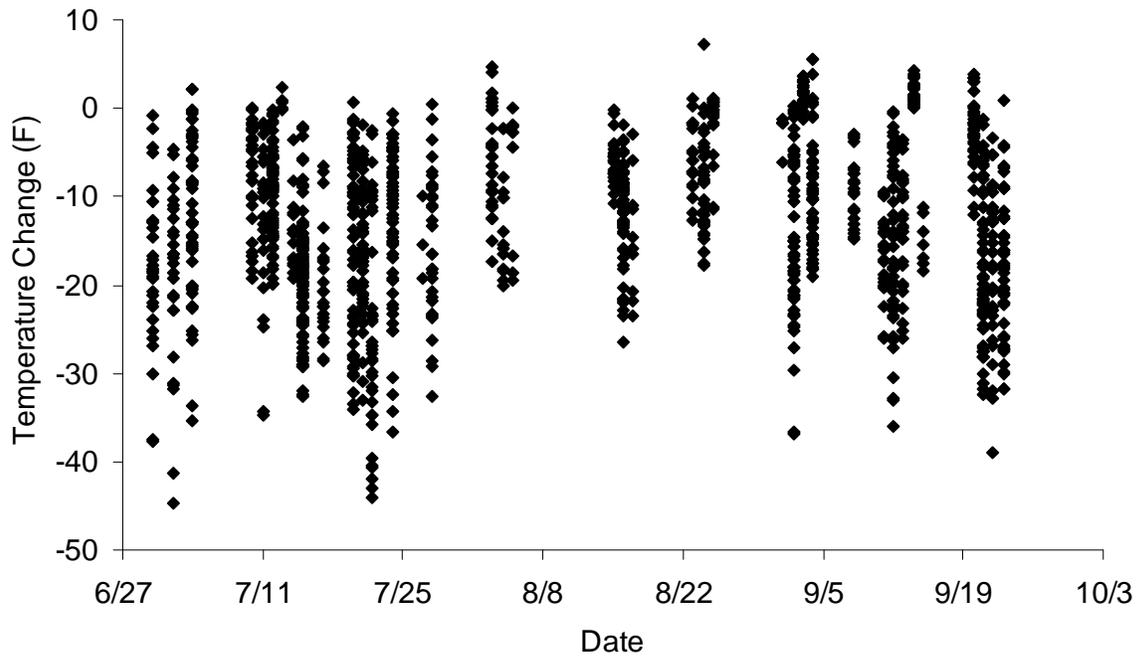


(b)

Figure 14. (a) The variation in the number of pikas counted in each survey area during repeat surveys with the date of the survey ($n = 21$). The survey area was included as a random effect in the model and the black line represents the fit of the population model. (b) The standard error of the average count for each survey area based on data from replicate surveys against the average number of pikas counted for each survey area ($n = 8$). The line of best fit is also depicted.

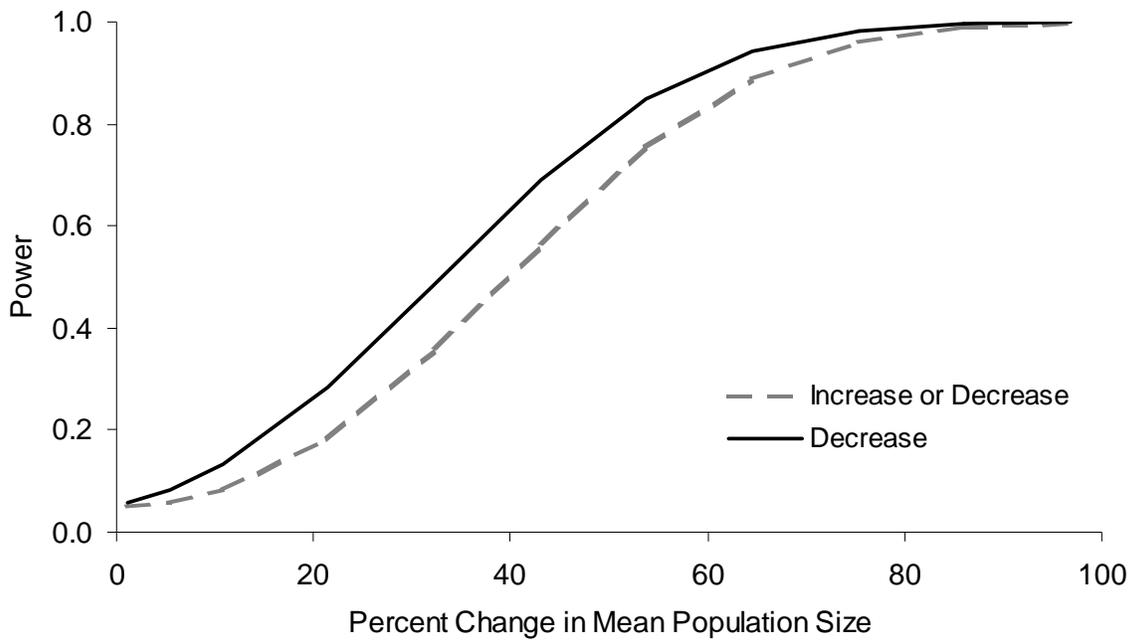


(a)

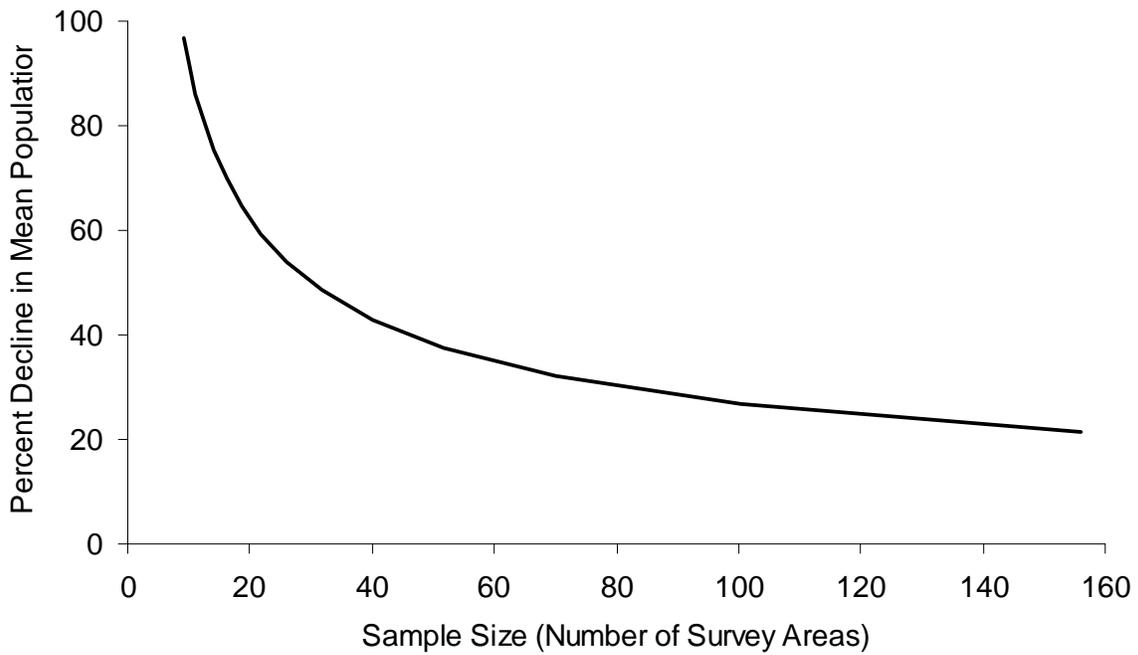


(b)

Figure 15. Variation in the temperature change ($^{\circ}\text{F}$) recorded between the talus surface and sub-surface ($n = 1,306$) (a) with varying surface temperature ($^{\circ}\text{F}$), and (b) with the date. Temperature data was collected from 1-m^2 plots in talus patches.

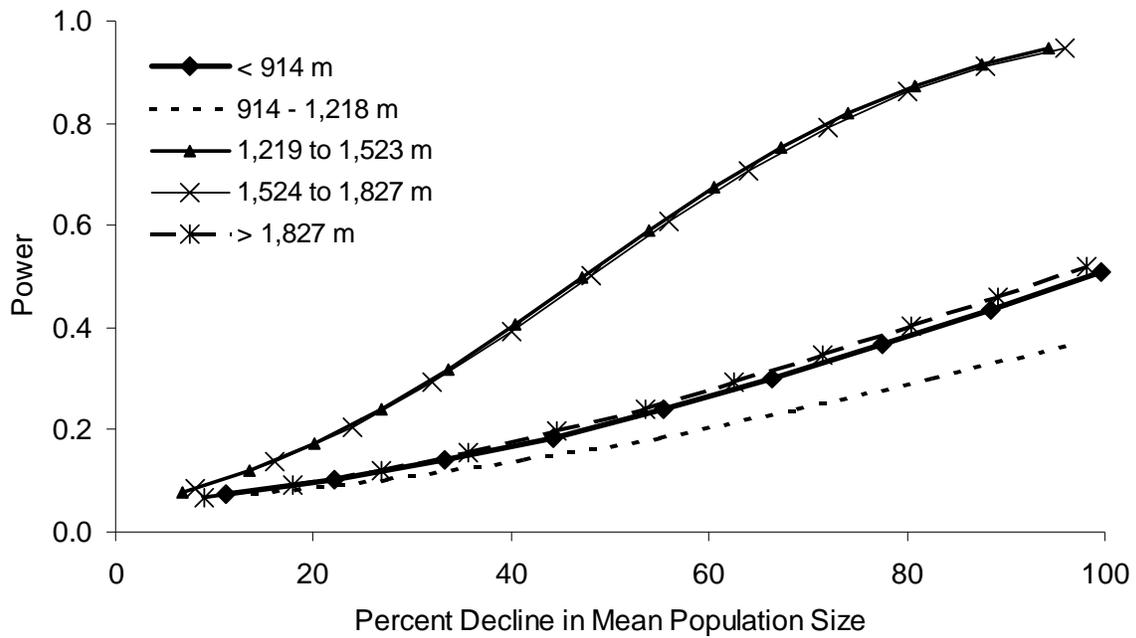


(a)

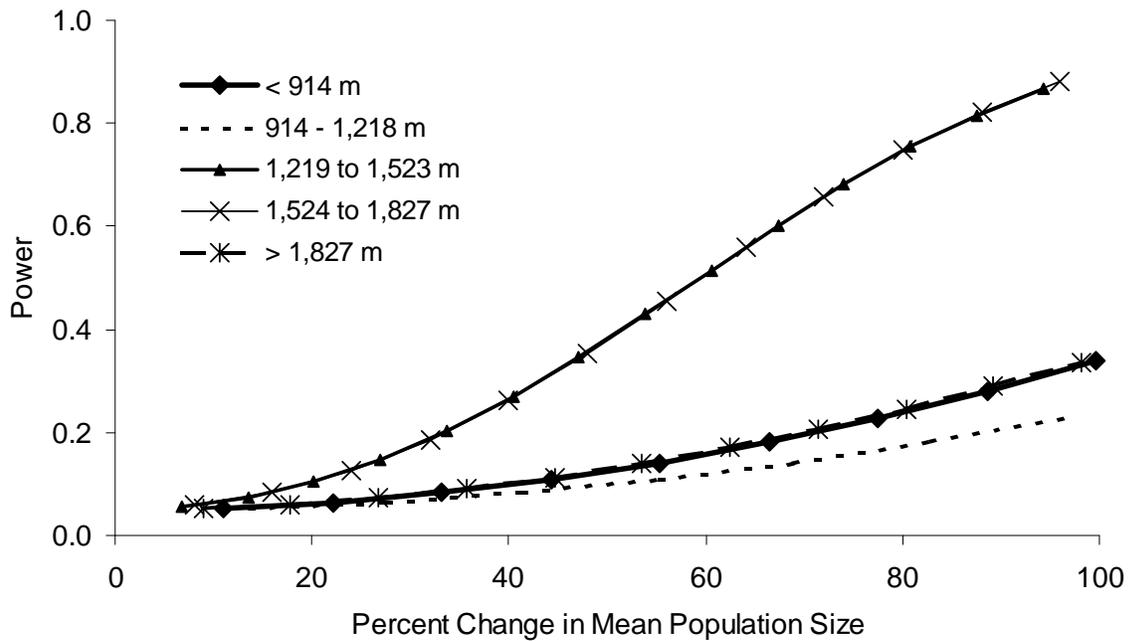


(b)

Figure 16. The relationship between the (a) power to detect a change (i.e., increase or decrease) or decline in mean pika abundance and the percent change in mean pika population size per survey area, and (b) detectable percent decline in mean population size and sample size.



(a)



(b)

Figure 17. Variation in the power to detect a (a) decline, and (b) change (i.e., increase or decrease) in mean pika population size per survey area for the five elevation strata (< 914 m; 914 to 1,218 m; 1,219 to 1,523 m; 1,524 to 1,827 m; > 1,827 m).

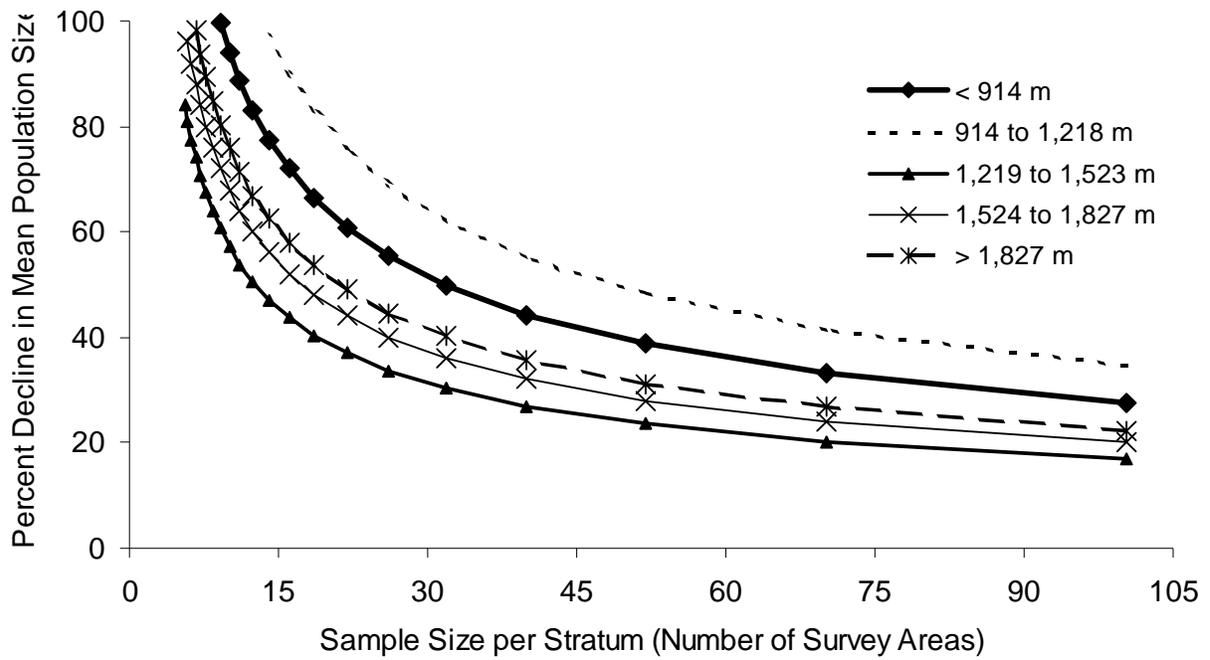


Figure 18. The change in the smallest detectable percent decline in mean pika population size per survey area for the five elevation strata with the sample size of each stratum. The elevation strata are < 914 m; 914 to 1,218 m; 1,219 to 1,523 m; 1,524 to 1,827 m, and > 1,827 m.

9. PARTNERSHIPS

This study was accomplished through contributions from Beartooth Wildlife Research, LLC, the North Cascades National Park Service Complex, and Seattle City Light. In-kind contributions from Beartooth Wildlife Research included: four months of effort from principal investigator Jason Bruggeman; use of a Jeep Wranger for field work and travel between North Cascades National Park from Farmington, MN; use of two computers, two printers, and one cell phone, and internet and long-distance phone connections. In-kind contributions from the North Cascades National Park Service Complex included 19 days (190 hours) of field work effort from biologist Roger Christophersen, use of a National Park Service vehicle to accommodate travel to and from trailheads during this effort, 212 person-days of housing at the Newhalem Research Station, and backcountry permits to reserve campsites near survey areas. In-kind contributions from Seattle City Light included access to wireless internet service from Newhalem, WA.

10. PUBLICATIONS

I am planning on preparing a manuscript about this study for submission to a peer-reviewed journal. The submission will likely occur in summer 2010.

11. APPENDICES

11A. APPENDIX A—ADDITIONAL TABLES AND FIGURES.

Table A1. The number of survey areas in the sampling universe within each of the 15 strata with each strata defined as a combination of based on a combination of mean survey area elevation (≤ 913 m; 914-1,218 m; 1,219-1,523 m; 1,524-1,827 m; $\geq 1,828$ m) and location relative to the divides (west; middle; east).

Stratum—mean elevation; divide location	Number of Survey Areas
≤ 913 m; east	24
≤ 913 m; middle	58
≤ 913 m; west	30
914-1,218 m; east	31
914-1,218 m; middle	68
914-1,218 m; west	25
1,219-1,523 m; east	36
1,219-1,523 m; middle	58
1,219-1,523 m; west	95
1,524-1,827 m; east	83
1,524-1,827 m; middle	105
1,524-1,827 m; west	84
$\geq 1,828$ m; east	84
$\geq 1,828$ m; middle	62
$\geq 1,828$ m; west	18

Table A2. Attributes of each of the 30 1-km² survey areas. For each survey area the following are provided: the total number of patches in the area; the total pika abundance enumerated during the survey; the date of the survey; the total perimeter of talus within the area, and the average elevation of the area.

SURVEY AREA NO.	NO. OF PATCHES	TOTAL PIKA ABUNDANCE	DATE OF SURVEY	TOTAL TALUS PERIMETER (m)	ELEVATION (m)
540	2	14	9/14/09	1677	1696
551	1	1	9/15/09	458	1021
600	1	65	9/12/09	9452	1768
608	8	47	9/13/09	5519	1665
888	3	22	8/13/09	2593	1621
1160	11	44	9/2/09	6513	1473
1230	7	45	9/3/09	2462	1371
1252	1	0	6/27/09	1378	1071
1367	1	5	7/2/09	2353	1528
1417	4	27	8/24/09	3369	1799
1453	3	33	8/22/09	2140	1342
1466	3	29	9/22/09	6695	1711
1561	2	9	8/26/09	708	1496
1568	4	15	7/21/09	7674	2000
1590	7	27	8/15/09	2374	1152
1699	3	11	7/15/09	929	1323
1763	2	21	8/23/09	4148	1756
1826	15	101	9/22/09	9480	1662
1917	1	18	8/17/09	1932	975
1921	3	52	9/27/09	4110	1577
2041	1	7	7/5/09	803	1709
2121	2	0	7/4/09	2334	764
2136	4	80	7/11/09	10500	2026
2138	7	0	7/4/09	1816	527
2177	9	5	7/12/09	3491	1966
2279	1	2	9/8/09	1027	351
2292	4	11	7/24/09	5024	654
2309	2	3	8/12/09	1731	484
2327	1	3	6/29/09	516	471
2406	2	10	8/6/09	1424	934

Table A3. Attributes of each of the 115 talus patches that were mapped within the 30 1-km² survey areas. For each patch the following are provided: the pika abundance enumerated during the survey; the date of the survey; the talus patch perimeter, and the elevation of the patch.

SURVEY AREA NO.	PATCH NO.	PIKA ABUNDANCE	DATE OF SURVEY	TALUS PERIMETER (m)	ELEVATION (m)
540	1	13	9/14/09	1302	1707
540	2	1	9/14/09	375	1685
551	1	1	9/15/09	458	1021
600	1	65	9/11/09	9452	1768
608	1	15	9/12/09	940	1723
608	2	23	9/12/09	3020	1661
608	3	3	9/12/09	390	1592
608	4	1	9/12/09	359	1624
608	5	2	9/13/09	330	1760
608	6	1	9/13/09	151	1762
608	7	1	9/13/09	215	1610
608	8	1	9/13/09	115	1588
888	1	19	8/13/09	2140	1643
888	2	0	8/3/09	105	1549
888	3	3	8/13/09	348	1669
1160	1	25	9/1/09	3878	1464
1160	2	0	9/1/09	178	1426
1160	3	0	9/1/09	94	1427
1160	4	4	9/1/09	317	1513
1160	5	2	9/1/09	305	1582
1160	6	1	9/2/09	60	1552
1160	7	2	9/2/09	265	1473
1160	8	4	9/1/09	321	1501
1160	9	1	9/1/09	238	1496
1160	10	3	9/1/09	697	1393
1160	11	2	9/1/09	162	1380
1230	1	27	9/3/09	1329	1393
1230	2	10	9/3/09	602	1333
1230	3	1	9/3/09	135	1350
1230	4	1	9/3/09	46	1329
1230	5	5	9/3/09	304	1445
1230	6	0	9/3/09	23	1374
1230	7	1	9/3/09	22	1374
1252	1	0	6/27/09	1378	1071
1367	1	5	7/2/09	2353	1528
1417	1	3	8/24/09	241	1883
1417	2	3	8/24/09	298	1754
1417	3	13	8/24/09	2036	1852

Table A3—continued

1417	4	8	8/24/09	794	1706
1453	1	18	8/22/09	970	1356
1453	2	3	8/22/09	150	1325
1453	3	12	8/22/09	1020	1346
1466	1	10	9/22/09	1289	1551
1466	2	10	9/22/09	727	1614
1466	3	9	9/22/09	4678	1967
1561	1	3	7/20/09	243	1521
1561	2	7	8/26/09	464	1472
1568	1	15	7/21/09	7486	2080
1568	2	0	7/21/09	80	1942
1568	3	0	7/21/09	66	1995
1568	4	0	7/21/09	42	1984
1590	1	14	8/15/09	939	1110
1590	2	2	8/15/09	284	1230
1590	3	0	8/15/09	417	1172
1590	4	3	8/16/09	382	1126
1590	5	6	8/16/09	222	1226
1590	6	1	8/16/09	73	1090
1590	7	1	8/16/09	59	1108
1699	1	4	7/15/09	413	1334
1699	2	3	7/15/09	210	1363
1699	3	4	7/15/09	307	1271
1763	1	21	8/23/09	3222	1785
1763	2	0	8/23/09	926	1728
1826	1	11	9/20/09	504	1538
1826	2	8	9/20/09	187	1625
1826	3	11	9/20/09	576	1605
1826	4	10	9/21/09	363	1690
1826	5	4	9/21/09	299	1746
1826	6	3	9/21/09	568	1796
1826	7	29	9/21/09	4489	1858
1826	8	2	9/21/09	731	1671
1826	9	1	9/21/09	215	1716
1826	10	0	9/21/09	75	1754
1826	11	1	9/22/09	84	1487
1826	12	6	9/22/09	515	1493
1826	13	2	9/23/09	90	1705
1826	14	13	9/23/09	687	1671
1826	15	0	9/23/09	97	1581
1917	1	18	8/17/09	1932	975

Table A3—continued

1921	1	50	9/26/09	4001	1614
1921	2	1	9/26/09	55	1572
1921	3	1	8/7/09	53	1545
2041	1	7	7/5/09	803	1709
2121	1	0	7/4/09	822	892
2121	2	0	7/4/09	1512	635
2136	1	24	7/10/09	4756	2130
2136	2	1	7/10/09	93	1952
2136	3	10	7/11/09	686	1903
2136	4	45	7/11/09	4965	2118
2138	1	0	7/4/09	204	583
2138	2	0	7/4/09	384	535
2138	3	0	7/4/09	523	463
2138	4	0	7/4/09	113	398
2138	5	0	7/4/09	375	373
2138	6	0	7/4/09	143	664
2138	7	0	7/4/09	75	677
2177	1	5	7/12/09	1100	2032
2177	2	0	7/12/09	218	1849
2177	3	0	7/12/09	231	1859
2177	4	0	7/12/09	233	2021
2177	5	0	7/12/09	508	2011
2177	6	0	7/12/09	157	2081
2177	7	0	7/12/09	612	1956
2177	8	0	7/12/09	283	1932
2177	9	0	7/13/09	148	1955
2279	1	2	9/8/09	1027	351
2292	1	3	8/13/09	1683	582
2292	2	2	7/24/09	1064	702
2292	3	7	7/24/09	1749	831
2292	4	1	8/5/09	528	500
2309	1	3	8/12/09	959	472
2309	2	0	7/14/09	772	497
2327	1	3	6/29/09	516	471
2406	1	6	8/6/09	504	902
2406	2	4	8/6/09	920	966

Table A4. The sample size for each vegetation cover type for each of the five elevation strata (< 914 m; 914 – 1,218 m; 1,219 – 1,523 m; 1,524 – 1,827 m; > 1,827 m). The sample size corresponds to the number of times the cover type was recorded in 1-m² plots during habitat data collection in talus patches.

Stratum	< 914 m	914 - 1,218 m	1,219 - 1,523 m	1,524 - 1,827 m	> 1,827 m
Cover Type	SAMPLE SIZE				
Bryophytes	109	78	273	265	32
Cushion plants	0	1	38	134	48
Ferns	3	12	33	60	8
Forbs	2	17	54	109	53
Graminoids	3	9	61	149	51
Lichens	86	43	142	34	8
Shrubs	9	15	56	131	36
Trees	1	3	7	4	4

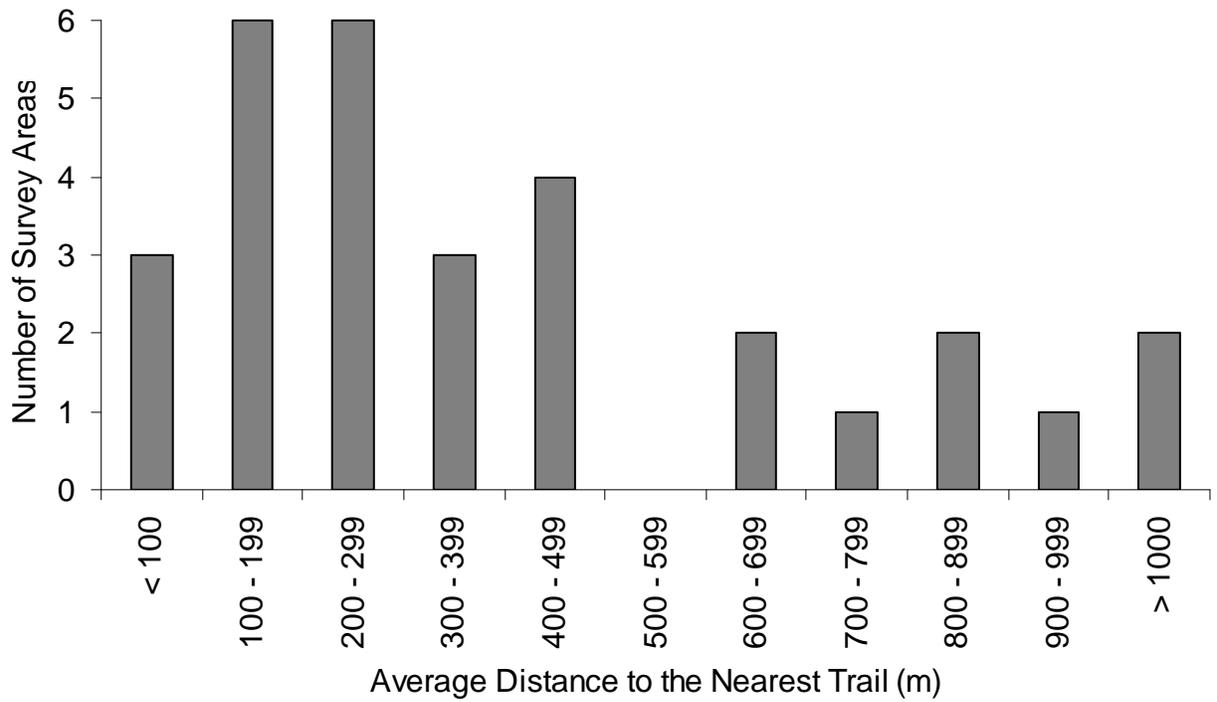


Figure A1. The distribution of the average distance to the nearest trail (meters) for the 30 1-km² survey areas.

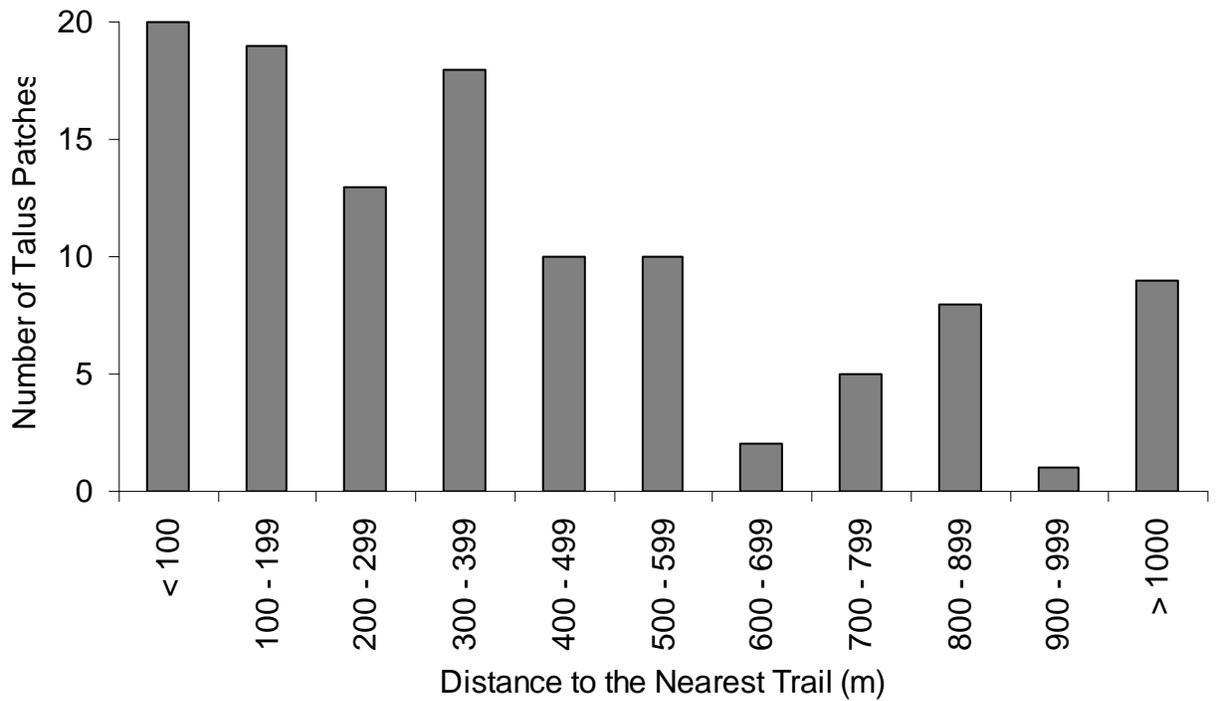


Figure A2. The distribution of the distance to the nearest trail (meters) for the 115 talus patches.

11B. APPENDIX B—BACKGROUND OF MODEL SELECTION USING AIC

This appendix provides a brief introduction to modeling and model selection using information-theoretic methods in the analysis of empirical data. I will use the modeling analysis that examined factors affecting pika abundance on the survey area scale to illustrate various points. Because the background behind information-theoretic methods is very detailed the interested reader should consult Burnham and Anderson (2002), which is considered to be the authoritative reference on the subject and provides the background for material below.

One begins by developing a set of candidate models that each represents a hypothesis to approximate the information contained in the data. The models consist of one or more covariates that are also hypothesized to explain some information in the data. In the case of the analyses completed for this report, regression models were used that consisted of additive combinations of covariates and interactions between covariates. For the survey area abundance analysis, my *a priori* model list consisted of 15 models (Table B1). The philosophy behind *a priori* modeling is that careful consideration has been put into what covariates to include in the models based on the system and biological rationale. This is in contrast to developing a model list that contains every possible combination of any variable measured, which Burnham and Anderson (2002) term “data dredging” that can lead to spurious results and correlations. Because biological systems are complex, there is not one “true model.” Rather, each model serves as an approximation to the truth and information-theoretic methods allow selection of a top model, and ranking and weighting of the remaining models from a candidate list of models.

After preparing an *a priori* model list, one fits the models and estimates covariate coefficients. In the case of the survey area abundance analysis, I used regression techniques to fit each of the 15 models. For each model, one calculates an Akaike’s Information Criterion (AIC) value. The AIC value is defined as $AIC = -2 \ln(L(\theta | y)) + 2K$, where \ln is the natural logarithm, $L(\theta | y)$ is the likelihood at its maximum point given estimated values of the covariate coefficients contained in the model (θ), and K is the number of parameters in the model. The value for K is often equal to the number of covariate main effects and interactions in the model plus the intercept. The AIC value provides an estimate of the expected relative distance between the fitted model and the unknown true mechanism that actually generated the data (Burnham and Anderson 2002). For small sample sizes, use of a corrected AIC value (AIC_c) is recommended (Burnham and Anderson 2002: p. 66).

Model No.	Model Structure
1	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area}$
2	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + DISTCAMP_{area}$
3	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + TMAX_{area}$
4	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + COVER_{area}$
5	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + SWEMAX_{area}$
6	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + DISTCAMP_{area} + TMAX_{area}$
7	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + DISTCAMP_{area} + COVER_{area}$
8	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + DISTCAMP_{area} + SWEMAX_{area}$
9	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + TMAX_{area} + COVER_{area}$
10	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + COVER_{area} + SWEMAX_{area}$
11	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + DISTCAMP_{area} + TMAX_{area} + COVER_{area}$
12	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + DISTCAMP_{area} + COVER_{area} +$ $SWEMAX_{area}$
13	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + COVER_{area} +$ $PERIMETER_{area} * COVER_{area}$
14	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + TMAX_{area} + COVER_{area} +$ $PERIMETER_{area} * COVER_{area}$
15	$ABUNDANCE_{area} = PERIMETER_{area} + ELEV_{area} + COVER_{area} + SWEMAX_{area} +$ $PERIMETER_{area} * COVER_{area}$

Table B1. The 15 a priori models that were evaluated for the survey area abundance analysis. Note that the intercept term and covariate coefficients are not depicted in the model structure. The response variable and covariates are defined in the main text.

After calculating an AIC (or AIC_c) value for each model, one then calculates the ΔAIC (or ΔAIC_c) value for each model (*i*), which is equal to ΔAIC_i = AIC_i – AIC_{min}, where AIC_{min} is the minimum value of AIC for a model from all models in the candidate list. Similarly, ΔAIC_{c,i} = AIC_{c,i} – AIC_{c,min}. By definition, the model estimated to be the best, or top, approximating model has an ΔAIC_i = ΔAIC_{min} = 0. The larger the ΔAIC value for a model, the less likely it is that the model is the best model given the data. For the 15 models evaluated as part of the survey area abundance analysis, model number 1 had the lowest AIC_c value of 224.74 and, therefore, had an ΔAIC_c = 0 (Table B2).

Model No.	K	AIC _c	ΔAIC _c	w
1	3	224.74	0.00	0.296
2	4	227.32	2.59	0.081
3	4	226.29	1.55	0.137
4	4	227.14	2.40	0.089
5	4	226.22	1.48	0.141
6	5	229.26	4.52	0.031
7	5	230.00	5.26	0.021
8	5	229.20	4.46	0.032
9	5	229.21	4.47	0.032
10	5	229.12	4.38	0.033
11	6	232.46	7.72	0.006
12	6	232.38	7.64	0.006
13	5	227.91	3.17	0.061
14	6	230.50	5.76	0.017
15	6	230.44	5.70	0.017

Table B2. Model results for the 15 *a priori* models that were evaluated for the survey area abundance analysis. The model numbers correspond to the models presented in Table B1. For each model, the number of parameters (K), AIC_c value, ΔAIC_c value, and Akaike weight (w) are provided.

Models that have an ΔAIC (or ΔAIC_c) value < 2 are considered to have a substantial amount of empirical support based on the data (Burnham and Anderson 2002). These models then provide the basis for any interpretation of significant statistical relationships between the response variable and covariates contained in the models. Models with an ΔAIC (or ΔAIC_c) value > 2 have considerably less support in the data and are omitted from further consideration or interpretation. For the case of the survey area abundance analysis, models 1, 3, and 5 had an ΔAIC_c < 2 and were the models I used to interpret the modeling results. Model 1 is considered to be the top approximating model, model 5 is the second best model, and model 3 is the third best model. One additional measure to determine the weight of evidence in favor of a particular model being the best model is the Akaike weight (w). The weight for each model (i) is defined as $w_i = \exp(-0.5 \cdot \Delta AIC_i) / \sum \exp(-0.5 \cdot \Delta AIC_r)$, where the summation is over all models in the candidate list from r = 1 to r = R, where R is the total number of candidate models (Burnham and Anderson 2002). When AIC_c is used instead of AIC, the ΔAIC_c value can be substituted for ΔAIC in the equation for the weight. By definition, the weight ranges from 0 to 1 and models

that have higher weight values have more support in the data. Also by definition, the model with an $\Delta AIC_c = 0$ will have the highest weight among all models in the candidate list. For the survey area abundance analysis, model 1 had a weight of 0.296 (Table B2). Models 3 and 5 had weights of 0.137 and 0.141, respectively (Table B2).

I presented the results of the survey area abundance modeling analysis in section 3C.2 on page 21 of the report. This is the paragraph I wrote:

There were three models with $\Delta AIC_c < 2$ for the *a priori* analysis with the top approximating model having a $w = 0.296$ and an explained deviance (Zuur et al. 2009) of 49.0%. All three models contained significant, positive $PERIMETER_{area}$ (Figure 12a) and $ELEV_{area}$ (Figure 12b) covariates with coefficient confidence intervals that did not overlap zero. The model averaged coefficient (Burnham and Anderson 2002) for $PERIMETER_{area}$ was 0.741 (SE = 0.310) and for $ELEV_{area}$ was 0.967 (SE = 0.412). The second ($\Delta AIC_c = 1.48$, $w = 0.141$) and third best models ($\Delta AIC_c = 1.55$, $w = 0.137$) also included $SWEMAX_{area}$ and $TMAX_{area}$, respectively. However, both covariates had confidence intervals that slightly overlapped zero with the coefficient for $SWEMAX_{area}$ being 0.329 (SE = 0.255) and for $TMAX_{area}$, -0.437 (SE = 0.344).

The first sentence describes how many models from the analysis had an $\Delta AIC_c < 2$ and provides the weight for the top model. Because no true R^2 value exists for negative binomial or Poisson regression, the explained deviance can be thought of as a pseudo- R^2 (Zuur et al. 2009). The second sentence lists the covariates that were statistically significant effects in the models with a P-value < 0.05 . The phrase “with coefficient confidence intervals that did not overlap zero” means the covariates were statistically significant. The third sentence presents coefficient estimates and standard errors for the perimeter and elevation covariates. The fourth sentence provides the ΔAIC_c values and weights for the second and third best models and that the second best model included the $SWEMAX_{area}$ covariate along with perimeter and elevation. The third best model included the $TMAX_{area}$ covariate along with perimeter and elevation. The phrase “had confidence intervals that slightly overlapped zero” means that while $SWEMAX_{area}$ and $TMAX_{area}$ had P-values > 0.05 , the covariates were “almost” statistically significant and did contribute to explaining some variability in the data.